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MECHANICS OF STIMULUS & RESPONSE GENERALIZATION IN SIGNAL DETECTION & PSYCHOPHYSICS: ADAPTATION OF STATIC THEORY TO DYNAMIC PERFORMANCE.

By

Blake A. Hutsell

B.S., Arkansas State University, 2003
M.A., Southern Illinois University, 2008

A Dissertation
Submitted in Partial Fulfillment of the Requirements for the
Doctor of Philosophy Degree

Department of Psychology
In the Graduate School
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DISSERTATION APPROVAL

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Approved by:

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AN ABSTRACT OF THE DISSERTATION OF

Blake A. Hutsell, for the Doctor of Philosophy degree in Psychology, presented on November 4, 2009, at Southern Illinois University Carbondale.

TITLE: MECHANICS OF STIMULUS & RESPONSE GENERALIZATION IN SIGNAL DETECTION & PSYCHOPHYSICS: ADAPTATION OF STATIC THEORY TO DYNAMIC PERFORMANCE.

MAJOR PROFESSOR: Eric A. Jacobs, Ph.D.

The area of perceptual decision-making research seeks to understand how our perception of the world affects our judgment. Laboratory investigations of perceptual decision-making concentrate on observers' ability to discriminate among stimuli and their biases towards reporting one stimulus more frequently than others. Choice theories assume that these performance measures are determined by generalization of reinforcement along both stimulus and response dimensions. Historically the majority of research has addressed situations in which the difference among stimuli and resulting consequences of a perceptual decision are static. Consequently, little is known about the dynamics of stimulus and response generalization. The present research investigated the dynamics of discrimination accuracy and response bias by frequently varying differences among stimuli and the outcomes for correct decisions.

In Experiment 1, four rats responded in a two-stimulus, two-response detection procedure employing temporal stimuli (short vs. long houselight presentations). Sample stimulus difference was varied over two levels across experimental conditions. A rapid acquisition procedure was employed in which relative reinforcer frequency varied daily. Shifts in response bias were well described by a behavioral model of detection (Davison & Nevin, 1999). Within sessions, bias adjusted rapidly to current reinforcer ratios when the sample stimulus difference was large, but not when the difference was small. In Experiment 2, three rats responded in a five-stimulus, two-response detection procedure employing temporal stimuli. Relative reinforcer frequency was again varied daily. Control by current session reinforcer ratios increased rapidly within sessions in a nearly monotonic fashion. Furthermore, response bias following each sample stimulus was observed within the first few trials of an experimental session. The speed of changes in response bias, especially following an unreinforced probe stimulus, provide strong support for an effective reinforcement process and suggest that this process may operate at a trial-by-trial level. In Experiment 3, three rats responded in a six-stimulus, two-response classification procedure. A repeated-acquisition procedure was employed in which the relationship between classes of short and long sample stimuli and their respective correct comparison locations reversed every 15 sessions. After several reversals, the probabilities of reinforcement for correct classification were also manipulated. In the majority of conditions across subjects, response bias reached half-asymptotic levels more rapidly than did discrimination accuracy. These findings provide some support for a backward chaining account of the acquisition of signal detection performance. An attention-augmented behavioral detection model accurately described the acquisition data; however parameter estimates expressing the probability of attending to sample and comparison stimuli differed widely among subjects.

The results of these experiments support the adaptation of dynamic research methodologies to the study of learning in perceptual decision-making tasks. Furthermore, discrimination performance and response bias adapt rapidly to frequent changes in reinforcement contingencies. Quantitative models formulated to describe static performance in detection procedures can be extended to predict dynamic performance. Some theoretical assumptions of these models were supported and others were violated. Overall, this research supports a renewed emphasis on learning in signal detection procedures and suggests that stable behavioral endpoints are at least as much a function of contingency variables as they are of sensory variables.

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CHAPTER 1

PSYCHOPHYSICS, SIGNAL DETECTION, AND OPERANT BEHAVIOR

Most would agree that if the world were exactly as we perceive it, then all our decisions would be perfectly accurate and the resulting consequences would be those we desire most. However, with experience, most of us become aware that the world often differs greatly from our perceptions. Moreover, we are aware that all too often our actions do not produce their intended effects. From our personal lives to our professional, the consequences of our decisions affect us as well as others. At times, the stakes are low; however, at other times the consequences of our actions can be dire. Many decisions require one to make a positive or negative decision based on the presence or absence of a particular event or piece of evidence. In this type of decision-making scenario, two types of mismatch between the true state of the world and our perceptions of it are possible. We can incorrectly conclude that the evidence for the event is satisfactory when it in fact is not and we can conclude the evidence is insufficient when it is actually adequate. The first error is called a false positive (false alarm) and the second a false negative (miss). Both are false assertions about the true state of the world and may be costly. Two independent facets of the world produce perceptual errors, the similarity of individual pieces of evidence and the consequences of positive and false judgments. For example, a quality control inspector must decide whether a textile meets or exceeds customer expectations. Clearly, no two pieces of fabric are identical and different customer bases have diverse demands. As a result, what the inspector judges to be of good quality depends on existing expectations and the fiscal consequences of incorrect designation of quality. Incorrect assignment of quality to a defective fabric will hurt the brand name. However, too high of a quality criterion is costly as much valuable material is discarded. The quality inspector must adopt a criterion that is neither too lenient nor to restrictive. To be successful, the individual must strike the right balance between erroneous judgments of poor quality fabric being treated as though it were high and high quality fabric mistakenly judged as poor. That is, the inspector must accept a certain frequency of errors; however, market forces will ultimately determine how strict the criterion must be if the manufacturer is to succeed. In other situations, the cost associated with each type of error is asymmetrical. For example, prognosis of a fatal disease and diagnosis of developmental disabilities carry with them greater costs of false judgments.

The area of perceptual decision-making research seeks to understand how the disparity between the world and our perceptions of it affect our judgments and how we might go about bringing the two into better alignment. This area of decision-making research has historically addressed situations in which the evidence and resulting consequences of a perceptual decision are static. The present dissertation attempts to study the dynamics of decision criteria by frequently varying evidence and decision outcomes. Specifically, by employing identification and categorization paradigms to study nonhuman behavior in a laboratory setting I hope to better understand how individuals learn to adopt a particular decision criterion. Additionally, a systematic understanding of the perceptual decision process may shed light on why individuals frequently make less than optimal judgments.

The following is intended to provide the reader with an introduction to the breadth of topics that inform the present work and simultaneously bring the goals of the present research into sharper focus. These topics include: research on choice (Herrnstein, 1970; Luce, 1963a), stimulus control (Dinsmoor, 1995; Guttman & Kalish, 1956; Honig & Urcuioli,1981), detection and identification (Luce & Galanter, 1963a; Luce & Green, 1974; Green, 1960), psychophysical scaling (Luce & Galanter, 1963; Thurstone, 1927a, 1927b), and mathematical treatments of the temporal patterning of responses (Blough, 1963; Killeen, Hall, Reilly, & Kettle, 2002; Luce, 1986; Link, 1992, McGill, 1963; Palya, 1992; Shull, 1991; Shull, Gaynor, & Grimes, 2001). Each topic has been studied extensively within two distinct, yet complementary traditions, the experimental analysis of behavior and psychophysics. Put most broadly, the focus of this research area is the processes by which distal environmental consequences come to have an affect upon an organism's behavior in a particular context. The present work is aimed at contributing to the methodological and empirical study of the dynamics of reinforcer effects of behavior-produced consequences that extend through stimulus and response dimensions to affect *different* classes of behavior at other times and in the presence of *different* stimuli (Hineline, 1993; Killeen, 1992; 1994).

This first chapter is intended to provide a general background on an area of research that has evolved over the last 40 years out of a union of psychophysics and the experimental analysis of behavior. First, I provide an overview of some commonly employed procedures and introduce prominent measures of performance taken from signal detection theory. Next, I will discuss research and theory that has mostly been informed by non-human research conducted in the tradition of the experimental analysis of behavior. These sections concentrate on theory development, specifically quantitative formulations of performance in signal detection, identification, and matching-to-sample procedures. The introductory section concludes with a discussion of the goals of this dissertation and outlines future research. Each subsequent chapter contains a review of the literature deemed most pertinent to each experiment.

Signal Detection: Accuracy and Bias.

One of the simplest psychophysical procedures is sometimes called a correspondence experiment (Macmillan & Creelman, 1991). In such a procedure, a correspondence is said to exist between the stimuli presented and responses available. That is, for each stimulus presented to the subject, a single response corresponds to that stimulus. The simplest form of correspondence experiment is the one-interval design. In the one-interval design, a single stimulus representing one of two possible classes of stimuli is presented to the subject on every trial. The subject's task is to identify the stimulus as being a member of one class or the other. The one-interval design is equivalent to the "yes-no" detection experiment. The "yes-no" task has been historically labeled as such due to its early use in absolute identification, where subjects were sometimes presented with a stimulus plus background noise or just background noise alone.

In Figure 1.1, the "yes-no" or "go, no-go" task is diagrammed as the classic absolute identification task where a stimulus plus noise is presented or noise alone is presented to the subject. In the absolute identification task, however, the concurrently available response (B_2) indicating noise alone is sometimes not explicitly measured. Alternatively, in a standard 2-stimulus, 2-response recognition task (Figure 1.1), subjects are presented with one of the two possible stimuli (S_1 or S_2) on each trial. One type of response (a B_1 response, e.g., a right button press) is deemed correct on S_1 trials and the other type of response (a B_2 response, e.g., a left button press) is deemed correct on S_2 trials. Feedback on the accuracy of the subjects' performance is typically given in the form of payoffs for correct responses and/or penalties for incorrect responses.

There are two key measures of performance in such procedures: the frequency with which subjects respond correctly and the frequency with which subjects make one type of response more frequently than others. The former measure is accuracy which ostensibly relates to the sensory aspects of the procedure, and the latter measure is called response bias and relates to decision variables such as payoffs or information feedback for correct and incorrect responses, respectively. These two primary measures of performance in a "yes-no" task can be visualized by plotting a receiver operating characteristic (ROC) function. Briefly, the ROC curve is a plot of the probability of the subject responding "yes" a signal was present plotted on the y-axis and the probability of saying "yes" when the noise alone was present plotted on the x-axis. The top graph of Figure 1.2 is a plot of a standard ROC curve with four levels of accuracy or *sensitivity*. The hit and false alarm probabilities have been plotted as their z transforms and are thus linear in these coordinates. Perhaps the most widely used measure of sensitivity (assuming an equal variance model) is d' as indexed by the distance of each line from the major diagonal and given by the equation:

$$d' = z(H) - z(FA) \tag{1.1}$$

where *z* is the inverse of the Gaussian probability density function and *H* and *FA* are the hit and false alarm probabilities (see Fig. 1.1), respectively (MacMillan & Creelman, 1991; Swets, 1986a, 1986b). The points lying along each line in Figure 1.2 would result from biasing manipulations such as instructions, unequal payoffs, or unequal penalties (Voss, McCarthy, & Davison, 1993). Each data point lying upon the same line indicates varying degrees of bias with a constant level of accuracy or sensitivity; a condition called isosensitivity (Luce, 1963a). Specifically, the measure of bias used to generate the points in Figure 1.2 is given by the criterion location measure *c*. This measure is calculated as:

$$c = -\frac{1}{2}\left[z(H) + z(FA)\right] \tag{1.2}$$

where all notation is as above. The bottom graph of Figure 1.2 is a plot of a z-transformed ROC curve with four levels of bias given by *c* indicated in the figure. The distance from the minor diagonal, which is indicated as a criterion value of zero, indexes the degree of bias and points lying the same distance from the minor diagonal at different levels of sensitivity satisfy a condition called isobias. Thus, the isobias curve is the complement of the isosensitivity curve. Isobias curves result from a biasing manipulations being held constant, while the signal to noise ratio is varied across experimental conditions.

Signal Detection as Operant Behavior.

Nevin's (1969) review of Green and Swets' (1966) foundational text on signal detection theory provided the conceptual bridge between the human psychophysics and nonhuman learning laboratories that continues to provide a framework for the study of the discriminated operant (Davison & Nevin, 1999; Shull, 1999; White & Wixted, 1999). Nevin pointed out important methodological similarities between the two disciplines and provided an analysis of response bias by extending the matching law treatment of choice in concurrent schedules of reinforcement (Catania, 1963a, 1963b, 1966; Herrnstein, 1961; Pliskoff, Shull, and Gollub, 1968).

Nevin recognized that the standard "yes-no" signal detection experiment of psychophysics (Bush, Galanter, & Luce, 1963) resembles a complex schedule of reinforcement (Ferster & Skinner, 1957). The 2x2-detection task is commonly treated as a variant of the matching-to-sample (MTS) task in the learning literature (Catania, 1998). Nevin suggested that the "yes-no" procedure is a concurrent schedule of reinforcement (B_1 and B_2 available simultaneously) within the context of a multiple or mixed schedule of reinforcement depending on the similarity of S_1 and S_2, respectively (see also Nevin, 1981). Multiple and mixed schedules of reinforcement (Ferster & Skinner, 1957) are composed of successively presented component reinforcement schedules, in which the transitions between each schedule are either signaled (i.e., multiple schedule) or unsignaled (i.e., mixed schedule). Thus, the "yes-no" task exists within the continuum of multiple-to-mixed concurrent schedules of reinforcement. When S_1 is not discriminable form S_2, conditions approximate a mixed schedule. When S_1 is highly discriminable from S_2, conditions approximate a multiple schedule.

The most enduring contribution of Nevin's (1969) review was his reanalysis of some data presented by Green and Swets (1966). The data reported by Green and Swets were obtained from a single subject in an auditory "yes-no" task. In the procedure from which the data were taken, the strength of an auditory signal remained constant while the probability of signal presentation or the relative payoffs for responding "yes" were varied to generate a receiver operating characteristic (ROC) function. Nevin's reanalysis demonstrated that the probability of a "yes" response was approximately equal to the relative frequency of payoff for responding "yes". Nevin speculated that the matching relation he found must depend in some way on the strength of the signal presented to the subject. The demonstration of matching of response to reinforcer proportions in a signal detection procedure by Nevin (1969) would form the basis of modeling efforts for the next two decades. However, his suggestion that the strength of the signal and reinforcement contingencies be treated similarly would not be investigated for many years (Davison & Nevin, 1999; Nevin, 1981).

A Matching Model of Detection.

Following Nevin's (1969) lead, Davison and Tustin (1978) presented a model for performance in signal detection procedures based upon the generalized matching law (Baum, 1974; 1979; Herrnstein, 1961). Davison and Tustin provided a choice-based model of detection performance that assumes that stimulus and payoff manipulations are independent sources of response bias. Therefore, the isosensitivity curve (Fig. 1.2), which is often obtained from subjects in studies of detection performance (Green & Swets, 1966; Macmillan & Creelman, 1991; Nevin, 1969; 1981), is the result of variation in payoffs at a constant level of stimulus difference, while the isobias curve results from variation in stimulus differences at constant relative payoffs. Although the model has been shown to be inadequate, it is an important historical development and thus foreshadows future efforts to model bias from a matching law-based approach.

Davison and Tustin's (1978) model predicts that choice among response alternatives in a 2-stimulus, 2-response detection task is independently determined by the reinforcer frequency ratio and the physical difference between the sample stimuli. The equation for predicting performance on S_1 trials is

$$\log\left(\frac{B_{11}}{B_{12}}\right) = a_r \log\left(\frac{R_{11}}{R_{22}}\right) + \log c + \log d \qquad (1.3a)$$

and the equation for performance on S_2 trials is

$$\log\left(\frac{B_{21}}{B_{22}}\right) = a_r \log\left(\frac{R_{11}}{R_{22}}\right) + \log c - \log d \qquad (1.3b)$$

where B*ij* and R*ij* are the response and reinforcer frequencies identified by the stimulus (S_1 or S_2) and response alternative (B_1 or B_2) to which it occurs (see Fig. 1.2). The parameter a_r, measures the extent to which variation in the reinforcer frequency ratio produces changes in the response ratio. Note that the log *d* and log *c* parameters are not the same as the *d'* and *c* parameters of detection theory, although the parameters do measure somewhat similar aspects of performance. The parameter log *d*, measures a constant preference towards making a correct response, which depends upon the difference between S_1 and S_2. Thus, the signs are opposite in the two equations. In the generalized matching approach, log *c* measures any constant bias towards one response alternative that is independent of variation in the reinforcer frequency ratio (i.e., side or comparison color preference, unequal response force requirements; see Baum, 1974; 1979). The parameters log *d* and log *c* are assumed to be independent sources of preference in a detection task. That is, discrimination, as measured by log *d*, must be equal in both equations and log *c* is a measure of any residual preference due to variables other than reinforcer frequency or stimulus difference.

The chief prediction following from Davison and Tustin's (1978) formulation is that stimulus and reinforcer variables are independent sources of bias in a detection task. This assumption of independence can be seen when Equations 1.3a and 1.3b are added to produce an equation that predicts overall response bias, log *B*. Davison and Tustin's equation for measuring overall response bias, after algebraic simplification, is:

$$\log B = 0.5 \log\left(\frac{B_{11} \cdot B_{21}}{B_{12} \cdot B_{22}}\right) = a_r \log\left(\frac{R_{11}}{R_{22}}\right) + \log c \tag{1.4}$$

where all variables, variable subscripts, and parameters are as above. Note that in the derivation of Equation 1.4, the stimulus bias term (log *d*) has dropped out of the equation. Therefore, Davison and Tustin's equation for bias states that the relative frequency of making a B_1 or B_2 response in the presence of S_1 or S_2 is a linear function of the relative frequency of reinforcers for correct responses and uncontrolled sources of bias. Furthermore, the equation predicts that bias is independent of discrimination between S_1 and S_2. While adding Equations 1.3a and

1.3b provides an overall measure of bias in a detection task, subtraction of the two equations gives an overall measure of discrimination. Davison and Tustin's equation for measuring discrimination performance is:

$$\log d = 0.5 \log\left(\frac{B_{11} \cdot B_{22}}{B_{12} \cdot B_{21}}\right) \tag{1.5}$$

where B*ij* are the response frequencies as defined above. The measure log *d* is the geometric mean of the ratio of correct and error responses. The antilog of this measure of discrimination is the inverse of the confusion measure *η* derived from choice theory (Luce, 1963; Shepard, 1957, 1958a). Note that the terms indicating the frequencies of reinforcers for each correct response do not appear in Equation 1.5. Therefore, the detection model of Davison and Tustin predicts independence between bias and discrimination performance in a detection task.

Initial research conducted and analyzed according to Davison and Tustin's model supported the predicted independence of bias and discriminability. McCarthy and Davison (1979) reported a study in which the physical difference between S_1 and S_2 was held constant and the frequency of reinforcement for correct responses was varied across several conditions. They reported that as bias (log *b*) varied directly with the reinforcer ratio, point estimates of log *d* were constant; therefore bias and discrimination were independent. McCarthy and Davison (1980a) again varied the relative frequency of reinforcers for correct responses, but over two levels of stimulus difference across conditions. They also reported that bias (log *b*) and discrimination (log *d*) were independent. Subsequently, McCarthy and Davison (1980b) reported that these measures were independent over a larger range of variation in stimulus difference.

Although early research supported the independence assumption of Davison and Tustin's model (for review see Davison & McCarthy, 1988; McCarthy & Davison, 1981a, 1981b), later, more extensive studies reported interactions between bias and discriminability. McCarthy and Davison (1984) carried out a large parametric study in which they varied the reinforcer ratio across three levels at each of five levels of difference between S_1 and S_2 in a detection task with pigeons. McCarthy and Davison also studied the effects of two procedures for scheduling reinforcers for correct responses (see also Stubbs, 1976). The first procedure called a controlled reinforcer ratio procedure, sets up a reinforcer for a correct response and assigns no further reinforcers until the appropriate response occurs and the assigned reinforcer is obtained. In the uncontrolled reinforcer ratio procedure, the scheduling of reinforcers for each correct response is independent of the other. In the choice literature, these two procedures for scheduling reinforcers concurrently are referred to as independent (Herrnstein, 1961) and dependent schedules (Stubbs & Pliskoff, 1969), respectively. McCarthy and Davison (1984) found that the relation between bias and discriminability depended upon the scheduling arrangement. In their controlled reinforcer ratio procedure (dependent schedule), estimates of bias remained constant as the sample stimuli where made more different, thus replicating previous work. In the uncontrolled reinforcer ratio procedure (independent schedule), however, bias was greater in the conditions of lower stimulus difference. That is, under the uncontrolled procedure, subjects showed a stronger bias towards the response alternative with the higher reinforcer rate when discrimination was poor.

Two points should be made regarding the findings of McCarthy and Davison (1984) and others like them (Alsop & Davison, 1991; Godfrey, 1997; Nevin, Cate, & Alsop, 1993). Although McCarthy and Davison's (1984) study was the first to show an interaction between bias and discriminability, other studies subsequently replicated these findings (Alsop & Davison, 1991; Godfrey, 1997). Currently, the reasons for this interaction are not well understood (Alsop, 1991, 1998; Alsop & Rowley, 1996; Alsop & Porritt, 2006). First, the interaction between bias and discriminability has subsequently been obtained using both uncontrolled (McCarthy & Davison, 1984) and controlled (Alsop & Davison, 1991) reinforcer ratio procedures (for discussion see Alsop & Porritt, 2006). Second, the sensitivity parameter, a_r in Equation 1.4 provides no insight into the possible mechanisms responsible for changes in bias. Although the Davison-Tustin model had some early success, recent research has shown the model to have serious limitations.

The fact that the assumption of independence has not held in at least some circumstances however, is troubling. Furthermore, the model cannot account for data from studies in which reinforcers for error responses have been arranged (Davison & McCarthy, 1980b; Nevin, Jenkins, Whittaker, & Yarensky, 1982). Perhaps most importantly, there is no obvious way to extend the model to procedures with more than two stimuli (Davison, 1991; Davison & McCarthy, 1987; 1989).

A Detection model of Choice.

Alsop (1991) and Davison (1991) independently introduced a detection model that predicts an interaction between bias and discriminability (Davison & Nevin, 1999). Their model is based upon an earlier model of choice proposed by Davison and Jenkins (1985). The model assumes that each response available to the subject in the detection task is affected by reinforcement for correct responses to the extent that the sample stimuli and response alternatives are similar to one another. For the case of 2-stimulus, 2-response detection, the equation describing performance in the presence of S_1 is written:

$$\log\left(\frac{B_{11}}{B_{12}}\right) = \log\left(\frac{R_{11} + \dfrac{R_{22}}{d_s d_r}}{\dfrac{R_{11}}{d_r} + \dfrac{R_{22}}{d_s}}\right) + \log c \tag{1.6a}$$

and for performance in S_2:

$$\log\left(\frac{B_{21}}{B_{22}}\right) = \log\left(\frac{\dfrac{R_{11}}{d_s} + \dfrac{R_{22}}{d_r}}{\dfrac{R_{11}}{d_s d_r} + R_{22}}\right) + \log c \tag{1.6b}$$

where B_{ij} and R_{ij} are the response and reinforcer frequencies as defined above. The parameters d_s and d_r are discriminability or distance measures and represent the discriminability between the stimuli d_s and response alternatives d_r, respectively (see Figure 1.1). The d_s and d_r parameters range from 1.0 to ∞, representing no discrimination to perfect control by the stimuli or response alternatives. Again, the constant log c is included to account for the biasing effects of any extraneous, constant choice-affecting variable.

Figure 1.3 demonstrates how the Alsop-Davison model predicts the interaction between Davison-Tustin measures of bias (log b) and discriminability (log d). The plot was generated by varying the relative frequency of reinforcers for correct responses over a wide range (100:1 to 1:100) while holding d_r constant and varying

$d_{s,}$ over three levels (25, 50, and 100). Next, the Davison-Tustin model of detection was fit to the data simulated by the Alsop-Davison model. The obtained values of sensitivity, which is an index of bias relative to the ratio of reinforcers (cf. Equation 1.4), and discriminability obtained from the fits of Equation 1.3 to the data generated by Equation 1.6, are plotted in Figure 1.3. Therefore, the model proposed by Alsop (1991) and Davison (1991), which treats discriminability among stimuli and responses symmetrically, predicts that the extent of bias observed depends on the level of discrimination given by d_s and can be seen if an overall measure of bias, analogous to log B in Equation 1.5, is obtained using Equation 1.6 and 1.6b (see Equation 8 of Davison & Nevin, 1999, for the derivation).

The most important theoretical difference between the model proposed by Alsop and Davison and the early Davison-Tustin model is the way in which stimulus distances produces changes in the frequency of error responses (B_{12} & B_{21}, respectively). According to the Davison-Tustin model, error responses are a function of reinforcers for correct responses (measured by a_r) and a constant level of bias towards the correct responses, given by a parameter relating the difference between the sample stimuli (log d). The model implies that error responses are due to the degree of stimulus generalization and does not include a role for response generalization or induction. Consequently, the model proposed by Davison and Tustin (1978) maintains the assumption of classical signal detection theory (Green & Swets, 1966) of independence between sensory and decision variables.

According to Alsop and Davison's model however, error responses are the result of the spread of reinforcement from other stimuli (d_s) and response classes (d_r).

To make the model's assumptions more explicit and to extend the model to more than two stimulus and response classes, the terms in Equations 1.6a and 1.6b can be replaced by primed variables, where for any cell (*m, n*) of a matrix (Fig. 1.1) with *s* stimuli and *r* responses:

$$R'_{m,n} = \sum_{r}^{i=1} \sum_{s}^{j=1} \left(\frac{R_{i,j}}{d_{sn,i} \cdot d_{rm,j}} \right) \tag{1.7}$$

with d_s and d_r ranging from 1 to ∞, so any cell is maximally similar to itself (i.e., $d_{sn,i} = 1$ and $d_{rm,j} = 1$). The primed reinforcer terms are the *effective* reinforcement for each response alternative. Therefore, Alsop and Davison's model assumes symmetrical effects on behavior when the disparity or physical difference among the sample stimuli and response definitions are manipulated. The logic dictated by Equations 1.6 and 1.7 follows up on the suggestions made by Nevin (Nevin, 1969; 1981) and discussed briefly above. To recognize Nevin's contributions, the model presented in Equations 1.6 and 1.7 will be referred to as the Davison-Nevin-Alsop (DNA) model hereafter (Davison & Nevin, 1999).

Alsop and Davison (1991) conducted a large parametric study in which they studied seven pairs of light intensities, which served as both samples in a detection procedure, and discriminative stimuli in a concurrent schedule of reinforcement. Across each procedure and within each stimulus set, the relative frequency of reinforcement was varied across at least three levels. Alsop and Davison reported that the DNA model provided an excellent fit to their data; however, they obtained a u-shaped relationship between d_s and d_r. Thus, although the model provides a good fit to the data, a consistent finding of parameter invariance has been lacking.

Furthermore, the finding of parameter covariation in the 2x2-detection procedure is perplexing, because the most successful extension of the DNA model has been from the simpler identification task to classification and related procedures involving more than two stimuli (Davison, 1991; 1996; Davison & McCarthy, 1987; 1988; 1994; Davison & Nevin, 1999; Krägeloh, Elliffe, & Davison, 2006).

Variations in Attending.

The most recent modification of the DNA model has been the addition of parameters measuring the probability with which subjects are assumed to attend to the relevant stimuli in stimulus detection and matching-to-sample procedures (MTS). Assuming that subjects do not attend to sample and comparison stimuli on every trial, Nevin, Davison, and Shahan (2005) provided a modified version of the DNA model that could account for : 1) previous data sets showing parameter covariation (Alsop & Davison, 1991), 2) effects of overall rate of reinforcement on stimulus discriminability (Schaal, Odum, & Shahan, 2000; Nevin, Milo, Odum, & Shahan, 2003), and 3) could be readily extended to describe performance in studies employing delayed matching-to-sample (DMTS) and related procedures (Nevin, Davison, Odum, & Shahan, 2007).

The modification of the DNA model presented by Nevin, Davison, and Shahan (2005) assumes that subjects' attend to the relevant sample and choice stimuli in a detection procedure depending on the rate of reinforcement for doing so. Specifically, the probability of attending to the sample stimuli $p(\mathrm{A}_s)$ is given by the expression:

$$p(A_s) = \exp \frac{-x}{(r_s / r_a)^b} \qquad (1.8)$$

where x is a parameter representing background distraction, scaled in units of the particular disruptor imposed (e.g., sessions of extinction), that interferes with attending to the sample and b is a sensitivity parameter (Nevin, 1992; Nevin & Grace, 2000). The term r_a is the session-based obtained overall rate of reinforcement. The term r_s is the rate of reinforcement for attending to the samples and is given by dividing the total number of reinforcers obtained in a session by the sum of the intertrial intervals (ITI) and sample duration. Thus, the time required to make a comparison choice is excluded from calculation of the rate of reinforcement for attending to the samples. A similar equation is used to predict the probability of attending to the choice alternatives or comparison stimuli, $p(\mathrm{A_c})$:

$$p(A_c) = \exp\frac{-z}{(r_c / r_s)^b} \tag{1.9}$$

where all parameters except z and r_c are as defined above. The parameter z represents background distraction, analogous to x in Equation 1.8, which interferes with attending to the comparison stimuli. The term r_c is the rate of reinforcement for attending to the choice or comparison stimuli and is given by dividing the total number of reinforcers obtained in a session by mean response latencies, plus the average retention interval in a DMTS procedure. Thus, the time required for sample presentation and the intertrial interval are excluded from calculation of the rate of reinforcement for attending to the comparison stimuli.

The model presented by Nevin and colleagues (2005) assumes that when subjects do not attend to the sample stimuli, d_s in Equation 1.6 is effectively 1.0. Likewise when subjects do not attend to the choice or comparison stimuli, d_r is 1.0. Behavior in a detection task, according to the model, is assumed to result from the subjects' behavior being governed by a combination each of the four possible states corresponding to attending to and not attending to the sample and choice stimuli. Therefore, as the session wide reinforcer rate increases, subjects are assumed to attend to sample and choice stimuli with greater frequency and behavior is governed by the original DNA equations.

Although the modification provided by Nevin and colleagues allows the original DNA model to account for some discrepant data sets and is consistent with some previous literature on attending in detection tasks (Berryman, Cumming, Cohen, & Johnson, 1965; Heinemann, Avin, Sullivan, & Chase, 1969; Wright & Sands, 1981), it is uncertain as of yet whether the extra parameters pay their way outside of applications to DMTS procedures. Moreover, in their reanalysis of archival data sets, Nevin and colleagues assumed only that $p(\mathrm{A}_s)$ was less than 1.0 without consideration of the actual obtained response latencies, which dictate $p(\mathrm{A}_c)$. Their insight, however, that on any given trial the subjects' behavior may not be under the control of either d_s, d_r, or both, is consistent with previous findings (Alsop & Rowley, 1996; Blough, 1996; Edhouse & White, 1998) and is taken up in the next section.

Learning and Detection.

The previous sections have discussed various models that have been proposed for signal detection performance. Obviously, each of them has had difficulties in accounting for some data sets (Alsop, 1998; Davison, 1991; Dusoir, 1975). Modifications to each of the models originating from the operant choice literature (Davison & McCarthy, 1988; Williams, 1988; 1994) have been made to the way in which the model quantifies biasing variables. In fact, it was originally thought that these models would provide a better treatment of bias than those developed by detection theorists (Nevin, 1969; Davison & Tustin, 1978; Davison & McCarthy, 1981).

It may be helpful to define three time scales over which the various models assume the sensory and decision variables operate in a detection situation. The origin of most modeling efforts in the operant choice tradition can be traced to classical signal detection theory (Green & Swets, 1966) and the matching law (Herrnstein, 1961; 1970). Both of these theoretical approaches are static and focus exclusively on aggregate or molar effects of stimulus similarity and relative payoff on performance measures obtained from highly trained observers. Other approaches highlight the role of between-trial sequential dependencies in detection procedures (Speeth & Mathews, 1961) and offer dynamic accounts of detection performance (Atkinson, Carterette, & Kinchla, 1962; Atkinson & Kinchla, 1965; Friedman, Carterette, Nakatani, & Ahumada, 1968). Many of these attempts however, have been limited to either restricted procedures or highly experienced subjects (e.g., Luce & Green, 1974). Finally, other accounts emphasize activities within a single trial in a signal detection task (Nevin, Davison, & Shahan, 2005; Link & Heath, 1975; Wright, 1991; 1992). The assumed operative temporal scale of each model originating in the operant choice literature is summarized below.

The model proposed by Davison and Tustin (1978) assumed that the variables affecting discrimination and bias are independent. Therefore, this model follows directly from signal detection theory as proposed by Green, Swets, Tanner, and Birdsall (Green, 1960; Tanner & Swets, 1954; Swets, Tanner, & Birdsall, 1961).

From the outset, signal detection theory has assumed that the sensory/perceptual and decision processes involved in signal detection and psychophysical experiments were independent of one another. Davison and Tustin's model followed this logic, but replaced previous measures of bias with one developed directly from the steady-state analysis of choice (Herrnstein, 1961; 1970). The model of Davison and Tustin (1978) is silent on the dynamics of detection performance. For present purposes, however, we may assume that the Davison-Tustin model predicts independent effects of sensory and decision variables on performance during any given trial.

Perhaps the greatest departure in theorizing in the operant choice literature comes from the DNA model (Alsop, 1991; Davison, 1991; Davison & Nevin 1999; Nevin, 1969; Nevin, 1981). The DNA model predicts that measures of bias will depend on discrimination performance (see Fig. 1.3). This model assumes that the perceptual and decision-making components of detection are derived from the same process, namely the spread of reinforcement across dimensions of stimulus and behavior. That is, the DNA model suggests a hierarchical behavioral unit (cf., Rescorla, 1992), in which the effect of response-produced reinforcing stimuli spread to other response and stimulus classes by virtue of similarity along those two dimensions. Therefore, a dynamic implementation of the DNA model suggests a diffusion or spread of effect of reinforcement along the dimensions of stimulus and response that depends on the local reinforcer value.

While the DNA model is the most successful and widely applicable model developed thus far in the operant-detection literature, it too has proven to be deficient in some cases (Nevin, Davison, & Shahan, 2005). The specific modifications to the

DNA model, rather than the authors' rationale for them, are most germane to the present discussion. The modified attending-augmented DNA model assumes that on a certain proportion of trials within an experimental session, the subject fails to attend to the sample stimuli, comparison stimuli or choice alternatives, or both. The consequences of this failure depend upon which stimulus is ignored. In their review, Nevin and colleagues needed to modify the probability of attending to the sample stimuli $p(\mathrm{A_s})$ to account for data from detection and MTS procedures with no delay between sample presentation and availability of the choice alternatives. The effect of changes in this parameter is to make d_s in Equation 1.6 equal to 1.0 (i.e., no sample discrimination) on some proportion of trials. If on some proportion of trials in each experimental session, a subject's behavior is not under control of the sample stimuli ($p(\mathrm{A_s}) < 1.0$), then are these trials of unvarying character or dependent on previous events? That is, do we assume that on some proportion of trials subjects disengage from the task or that performance on any trial is determined by events on the current trial as well as events on previous trials? Clearly then, we are obliged to study the circumstances under which subjects make choices completely based on biasing variables.

It may be that the earliest conceptualizations of psychophysical and signal detection performance were premature concerning the effects of biasing manipulations. That is, the assumption of independent sensory and decision processes may have been more a product of researcher's interests, rather than the determinants of the subject's performance. That is, early researchers in psychophysics were often exclusively interested in the pure sensory process and saw biasing variables as a nuisance that must to be controlled to reveal the true nature of the sensation. This suggestion may find support in discussions on the form of *the* psychometric function (Guilford, 1954; Thurstone, 1928). As suggested by Luce (1964), it was the advent of new methods in what came to be called local psychophysics that began to shift the prevailing view. On this view, methods such as those used to generate a receiver operating characteristic (ROC) suggested the importance of bias or contingency variables in determining performance in psychophysical tasks. Therefore, it is not surprising that many researchers did turn their attention to an analysis of the local effects of trial outcomes.

Early in the study of local psychophysics, a number of researchers suggested that under certain situations, performance on some trials is dependent on events in the preceding trial (Cross, 1973; Freidman & Carterette, 1964). In fact, several researchers proposed quantitative models to account for sequential dependencies and learning effects in signal detection procedures (Atkinson, 1963; Luce, 1963b; 1964). It seems quite strange that these effects have been largely ignored in the nonhuman laboratory. Furthermore, only now that steady state or molar performance models suggest the importance of local effects in detection procedures are these processes beginning to receive attention (Alsop & Rowley, 1996; Lie & Alsop, 2007; Ward & Odum, 2008).

It was the observation that on some occasions (Norman, 1963; Senders & Sowards, 1952; Shipley, 1961) sequential dependencies arise in detection performance and the great lengths experimenters went to in order to control response bias that led Luce (1964) to suggest a more thorough experimental analysis of the learning that takes place in psychophysical and detection experiments. Specifically, Luce suggested that at least two classes of learning models for detection studies could be examined. Two-process models are those which assume that learning involves both perceptual and decision changes across the course of a detection experiment (Atkinson, 1963; Kac, 1962). This type of model follows from the assumptions of classical signal detection theory (Green & Swets, 1966) which assumes that sensitivity and bias are independent. Therefore, according to Luce's classification scheme, the Davison-Tustin model is a steady-state version of a multi-process model. Another class of model, Luce called single-process models, are those which assume that the perceptual aspect of detection performance is subordinate to the feedback-driven learning process (Bush, Luce, & Rose, 1964; Schoeffler, 1965). Thus, according to Luce's classification scheme, the DNA model and its offspring are single process models.

The present research

The goal of the present work is to develop methods that allow for the study of the learning that takes place in signal detection and related procedures. The methods employed in the experiments presented here have been successful in recent attempts to study the dynamics of operant choice (Hunter & Davison, 1985; Mazur, 1996; Schofield & Davison, 1997; Grace, 2002a, 2002b; Grace, Bragason, & McLean, 2003). The experimental designs that have yielded some insight into the dynamics of choice typically vary choice affecting variables over a much shorter time scale than do steady-state counterparts (cf. Sidman, 1960). Such designs include varying relative reinforcer frequency every few sessions (Mazur, 1992, 1995, 1997), potentially each session (Hunter & Davison, 1985; Schofield & Davison, 1997; Grace, Bragason, & McLean 2003), or once or more within a single experimental session (Davison & Baum, 2000, 2002, 2003; Gallistel, Mark, King, & Latham, 2001). Findings from each of these designs have shown that choice may adapt at an extremely high rate to abrupt signaled and unsignaled changes in the relative frequency of reinforcement. Moreover, such methods have stimulated theoretical developments that encompass effects seen in both dynamic and traditional steady state procedures (Christensen & Grace, 2008; 2009; Grace & McLean, 2006). The present experiments were conducted with the expectation that similar methodological developments applied to the study of signal detection performance will reopen a once promising line of inquiry and produce similar advances. The research is composed of three experiments each employing similar methods to investigate dynamic aspects of signal detection performance.

The second chapter, "Rapid Acquisition of Bias in Signal Detection" presents the first attempt to implement a procedure that yields session-to-session changes in relative reinforcer frequency in a simple detection task. In Experiment 1, only 2 stimuli were presented in an experimental session, across conditions, however the durations of the sample stimuli were changed to create a condition in which discriminating the stimuli would be relatively easy and more difficult, respectively. The novel methodological contribution of the study was that relative reinforcer probability for correct detections varied randomly across sessions according to a pseudorandom binary sequence (PRBS). The first experiment suggests that this design, which has been implemented in simpler choice paradigms (Schofield &

Davison, 1997; Grace, Bragason, & McLean, 2003) may be useful in studying the dynamic properties of bias in a detection situation.

The third chapter, “Rapid Shifts in the Psychometric Function for Time” is an extension of the first experiment. Experiment 2 extends the application of the PRBS design from the simpler identification design to a classification task in which more than one stimulus is mapped to each of two available responses. The goal of Experiment 2 is to produce a psychometric function for each session under conditions of differential payoff. This experiment will allow a comparison between the speed of bias changes in simple and complex detection procedures. The design of Experiment 2 may prove to be the most expedient method to study large ranges of stimulus disparity and relative reinforcement variables in a signal detection task.

The fourth chapter, “Dynamics of Attending in the Repeated Acquisition of a Temporal Discrimination” again employs a classification design. The correct response location given a stimulus from one of two different classes and the relative frequency of reinforcement are varied every 15 sessions. This experiment is intended to provide information on the speed of repeated temporal discrimination acquisition between transitions of equal and unequal payoff for correct responses. In addition, Experiment 3 attempts to dissociate two hypotheses regarding the role of sample and choice stimuli in the repeated learning of a temporal discrimination.

Table 1.1 provides an outline of the experiments to be reported in the following chapters. Each experiment employed a detection task in which the duration of a stimulus presentation served as a sample stimulus. Common to all experiments is manipulation of the relative frequency of reinforcement for correct responses. In

Experiments 1 and 2, the relative frequency of reinforcement for correct responses was changed each session. Therefore, these two experiments explored the speed of changes in response bias when the relative frequency of reinforcement changed each session. In Experiment 3, both the relative frequency of reinforcement for correct responses and the mapping between stimulus class and correct response location changed every 15 sessions. Therefore, the first two experiments explored the speed and extent of changes in response bias while the stimuli to be discriminated are held constant and the third experiment manipulated stimulus and reinforcement variables simultaneously in order to investigate the development of both facets of detection performance.

In conclusion, the intended contribution of this dissertation is to begin a new research program utilizing considerably more dynamic experimental designs in the study of non-human signal detection performance. To this end, the goal of the research program consists of two phases: first to provide methodological advances and second to foreshadow the potential theoretical developments that are warranted by the present studies. The methodological goals can be met by obtaining aggregate data that are largely consistent with previous non-human studies of signal detection performance. The secondary goal of this work is to provide an accurate characterization of the time course of repeated acquisition of discrimination and bias in widely used variants of the classic “yes-no” detection procedure. Furthermore, the present experiments will provide substantial data sets on the local effects of both sensory and decision variables on detection performance, and perhaps provide a framework for an exclusively dynamic quantitative account of local reinforcer value on stimulus and response generalization (Shepard, 1958a) in various psychophysical choice procedures.

CHAPTER 2

RAPID ACQUISITION OF BIAS IN SIGNAL DETECTION.

Behavior allocation, measured as relative response rate, in concurrent variable-interval (VI), VI schedules of reinforcement is well described by the generalized matching law (Baum, 1974, 1979; Davison & McCarthy, 1988). For a two-alternative concurrent schedule the model is

$$\log\left(\frac{B_1}{B_2}\right) = a\log\left(\frac{R_1}{R_2}\right) + \log c \tag{2.1}$$

where B_1 and B_2 are the response frequencies and R_1 and R_2 are the frequencies of reinforcers obtained at alternatives 1 and 2. The parameter a is termed sensitivity to reinforcement (Baum, 1974; Lobb & Davison, 1975) and the parameter $\log c$ is inherent bias. Equation 2.1 has provided a very accurate description of choice in concurrent schedules of reinforcement, accounting for over 90% of the variance in log response ratios (Baum, 1979). Typically, the range of sensitivity to reinforcement is between 0.8-1.0 and inherent bias varies unsystematically around zero (Myers & Myers, 1979; Wearden & Burgess, 1982).

Miller, Saunders, and Bourland (1980) exposed pigeons to a switching-key concurrent schedule (Findley, 1958) and varied the relative frequency of reinforcement for responding to each alternative across conditions of the experiment. Between different groups of subjects, Miller and colleagues arranged different line orientations on the food key correlated with the various VI schedules. For the different groups of subjects the difference in line orientations was 0, 15, and 45 degrees. Miller and colleagues applied Equation 2.1 to their data and reported increasing estimates of sensitivity to reinforcement of 0.17, 0.32, and 1.0 with increasing differences in the line orientations correlated with the VI schedules. Alsop and Davison (1991) systematically replicated and extended Miller, Saunders, and Bourland's (1980) findings of changes in sensitivity to reinforcement with changes in the disparity of the discriminative stimuli correlated with the concurrent alternatives. Alsop and Davison (1991) analyzed their data according to both the generalized matching law and a contingency discriminability model proposed by Davison and Jenkins (1985).

Davison and Jenkins (1985) introduced a model for choice in concurrent VI, VI schedules that they argued was conceptually superior to the generalized matching law. Their model for a two-alternative concurrent schedule is written:

$$\log\left(\frac{B_1}{B_2}\right) = \log\left(\frac{R_1 + \frac{R_2}{d_r}}{\frac{R_1}{d_r} + R_2}\right) + \log c \tag{2.2}$$

where responses, reinforcers, and log c are as above. The parameter d_r is termed contingency discriminability and measures the extent to which the response-reinforcer relations control differential responding to each response alternative. Thus, as contingency discriminability decreases, reinforcers earned from each alternative have an increasingly non-differential effect on responding. The d_r parameter ranges from 1.0 to infinity, indicating zero to perfect discriminative control by the response reinforcer relations. Davison and Jenkins (1985) showed how their model could provide as accurate an account of concurrent schedule data as the generalized matching law. They further discussed how their model provided a conceptual mechanism to account for the findings of Miller and colleagues (1980; see also Alsop and Davison, 1991). That is, the contingency discriminability model explains the effects of stimulus control on choice as response generalization or induction between the two alternatives engendered by less that perfect discriminability between the concurrent response reinforcer relations.

Alsop (1987) and Alsop and Davison (1991) extended the contingency discriminability model to performance in signal detection procedures. In a standard 2-stimulus, 2-response detection task, subjects are presented with one of the two possible sample stimuli (S_1 or S_2) on each trial. One type of response (a B_1 response, e.g., a right lever press) is intermittently reinforced on S_1 trials and the other type of response (a B_2 response, e.g., a left lever press) is intermittently reinforced on S_2 trials. Figure 2.1 shows a 2x2 signal detection matrix and the effective reinforcer allocation according to Alsop and Davison's model (see also Davison & Nevin, 1999). Reinforcers are subscripted according to the cell of the matrix in which they occur, therefore reinforcers for $B_1 \mid S_1$ are designated R_{11} and $B_2 \mid S_2$ reinforcers are designated R_{22}. As in Davison and Jenkins model, the term d_r indicates the extent of discriminative control by the response reinforcer relations. The signal detection model involves a further parameter d_s, which is a measure of the degree of sample stimulus-based generalization of reinforcer effects on detection performance. Therefore, the Alsop-Davison detection model provides two sources for the generalization of the effects of reinforcement, one source based on the response-reinforcer relations and the other on the stimulus-response relations.

Alsop and Davison (1991) reported an extensive experiment, carried out with pigeons serving as subjects, in which they varied the stimulus difference between S_1-S_2 pairs in both a concurrent schedule and a detection task. In the signal detection conditions, they varied the difference between stimuli in a 2-stimulus, 2-response detection task across seven levels by holding the intensity of S_1 constant and changing the intensity of S_2 across conditions. The relative frequency of reinforcement for correct responses was varied over at least three levels at each level of stimulus difference. They reported that the contingency discriminability model gave an excellent account of their data. However, the d_r parameter varied in an inverse-U shaped pattern across levels of stimulus difference. That is, contingency discriminability varied as a function of variables that should only affect stimulus discriminability, d_s. Therefore, in Alsop and Davison's (1991) study, the model was unable to provide a parameter invariant account of their data (Nevin, 1984).

Recently, investigations of choice in concurrent schedules have been reported in which the relative frequency of reinforcement changes rapidly either within or between sessions (Davison & Baum, 2000; Hunter & Davison, 1985). Generally, these studies have found that relative response rate can adapt quickly to abrupt, unsignaled changes in relative reinforcer frequency. In Davison and Baum's (2000, 2002) procedure, where relative reinforcer frequency varies across seven levels within session, preference for the more frequently reinforced response emerges after the occurrence of a few reinforcers. Reports of control by changing reinforcement contingencies within a single session are also consistent with those that have shown control by contingencies changing from session to session (Schofield & Davison, 1997).

Hunter and Davison (1985) introduced a procedure for investigating rapid changes in preference where relative reinforcer frequency changes randomly between two values across sessions. Hunter and Davison found that variation of the relative frequency of reinforcers in a concurrent schedule according to a pseudorandom binary sequence (PRBS) produced rapid changes in preference. They also found that after several sessions of exposure to the PRBS that preference was only sensitive to the current session reinforcer ratio, with little discernable effects of previous sessions. Schofield and Davison (1997) reported a replication and extension of Hunter and Davison's (1985) study by extending the PRBS procedure to several reinforcer ratios and dependent versus independent schedules. Schofield and Davison (1997) provided an extended generalized matching model to describe control over responding in the current session by the current and previous nine sessions' reinforcer ratios. They reported that performance in the current session was mostly determined by the current session's reinforcer ratio and to a smaller degree by previous session reinforcer ratios. Schofield and Davison also reported that sensitivity to current session reinforcer ratios increased with extended exposure to the PRBS procedure. Finally, they reported no effect of the size of reinforcer ratio (8:1, 4:1, 2:1, 1:2, 1:4. 1:8) on sensitivity to current session reinforcer ratios. Based on these findings, Schofield and Davison (1997) argued that the PRBS design was a useful method for quick determination of sensitivity to reinforcement.

More recently, Grace, Bragason, and McLean (2003) have extended the PRBS design to concurrent-chained schedules of reinforcement. Specifically, in the first experiment of their study they varied the delay to reinforcement in one terminal link while holding the other constant. Thus, the immediacy ratio (reciprocal of delay ratio) changed randomly between sessions from 1:2 to 2:1. Grace and colleagues exposed their pigeons to three, 31-session sequences of the PRBS and reported that across sequences, preference came under increasing control of current session immediacy ratios (see also Grace & McLean, 2006). Extension of the PRBS design to concurrent chained schedules is important because it shows that preference is not only sensitive to random changes in primary reinforcer rate ratios, but also to changes in the value of stimuli correlated with primary reinforcement (Grace, 1994; Mazur, 2001, Nevin, Davison, & Shahan, 2005; Shahan, Podlesnik, & Jimenez-Gomez, 2006).

The present study sought to extend the PRBS method of varying relative reinforcer frequency to a signal detection procedure. Specifically, the relative frequency of reinforcement for correct responses in 2-stimulus, 2-response detection task employing temporal stimuli (short vs. long houselight presentations) was varied according to a 31-session PRBS. Across different PRBS presentations, the difference between the temporal sample stimuli was varied, creating two levels of discrimination difficulty. We asked whether detection performance and specifically if bias could come under control or random changes in the reinforcer ratio for correct responses. We also sought to determine the relationship between bias and discrimination under the PRBS design and these measures in studies employing designs that are more typical in this literature.

Hypotheses

1) Stimulus discriminability, measured as log *d*, will be lowest in conditions where the sample stimulus durations are 3.5 and 5.5 seconds, respectively.
2) By the end of each PRBS, response bias, measured as log *b*, will be primarily under control of the current session reinforcer ratio.
3) Within experimental sessions, bias will gradually shift from control by the previous sessions' to the current sessions' reinforcer ratio.
4) Based on previous findings, the speed and extent of changes in bias will be greater when discrimination accuracy is lower (i.e., stimulus durations of 3.5 & 5.5-s).

METHOD

Subjects

The subjects were four male Long Evans Hooded rats J85, J86, J87, and J88. All subjects were experimentally naïve at the beginning of the experiment. Food deprivation was held constant for each subject by post-session feeding (15g). The rats were housed individually and had free access to water when in their home cages in a vivarium with a 12:12 hr light/dark cycle (lights on at 6:00 a.m.). Sessions were conducted daily, at approximately the same time with few exceptions. Experimental sessions were conducted during the rats' light period.

Apparatus

The experiment was conducted in two standard operant conditioning chambers (Colbourn Instruments H10-11R-TC) measuring 29 cm high by 29 cm wide by 24 cm deep. The chambers were enclosed in a sound attenuating cubicle with white noise masking extraneous sounds.

On the front wall were two identical response levers, one 2.2 cm from the left wall and the other 2.2 cm from the right wall, 6 cm above the grid floor. The levers were 3.5 cm across and extended 2 cm into the chamber. A downward force on the lever of at least 0.3 N operated a switch that was connected to the lever and thereby generated a recordable response. Three small lights arranged in a horizontal row 3.5 cm apart center to center were located 2.5 cm above each lever. Only the center light was used in the current experiment. In the first chamber, the light above the left lever was lit white and the light above the right lever was lit blue. In the second chamber, the light above the left lever was lit red and the light above the right lever was lit green. A houselight, located centrally, at the top of the intelligence panel, provided general illumination of the chamber.

Centered on the front wall, 1.5 cm above the floor was a rectangular opening (4.1 cm high and 6.3 cm wide) through which the rat could obtain the reinforcer (sweetened condensed milk). The liquid dipper normally rested in a reservoir outside the chamber. The size of the dipper cup was 0.05 ml. The milk solution was made by diluting ordinary commercial sweetened condensed milk with tap water to make a milk and water mixture (one part milk/ three parts water).

One digital I/O card (Computer Boards, Inc.) Model # CIO-PDISO16 interfaced to an IBM-compatible computer located in an adjacent room controlled all experimental events and recorded data. All control software was written and compiled in Quickbasic®.

Procedure

Preliminary Training. Initially, left and right lever pressing was established via autoshaping. Once lever pressing was established, the rats were placed directly on the basic temporal discrimination procedure. Initially, each subject was trained on a procedure in which each correct short and long response was reinforced (FR1). That is, each right lever press following a 2-s houselight presentation and each left lever press following an 8-s houselight presentation were reinforced. Training sessions involved 150 discrete trials in which each trial began with illumination of the houselight for either 2 or 8 seconds. Upon termination of the houselight, the lights above each lever were lit and trials ended after either a lever press or 5 seconds, whichever occurred first. Each sample stimulus was presented 75 times in each session and stimulus presentation was randomized every block of 30 trials. Correct responses were reinforced with two, 2-s milk deliveries, followed by the intertrial interval (ITI) and incorrect responses led directly to the ITI. During the ITI all stimulus lights were turned off for a duration of 15-s, the ITI duration was constant throughout the experiment. Initial pretraining on the 2 versus 8 second stimulus durations lasted approximately 50 sessions. During the 50 pretraining sessions, the overall probability of reinforcement for correct responses was gradually decreased to 0.70. As the overall density of reinforcement was decreased, reinforcers were now arranged dependently (Stubbs & Pliskoff, 1969) such that a reinforcer assigned to a particular correct response was held and no other response could be reinforced until that reinforcer was obtained. Correct responses that were not eligible for reinforcement and incorrect responses led directly to the ITI. Between the first and second PRBS presentations, subjects were returned to the pretraining conditions and the stimulus durations were changed to 3 and 5.5 seconds. This training continued for approximately 25 sessions for each subject.

PRBS conditions. When accuracy on the 2 versus 8-s duration discrimination stabilized, as judged by visual inspection of graphical representations of the data, subjects were exposed to the first PRBS presentation. Under this condition, correct short (right lever presses following 2-s houselight presentation) and correct long (left lever presses following 8-s houselight presentation) responses continued to be reinforced according to a dependent schedule with an overall reinforcement probability of 0.70. Sessions lasted for 150 trials (75 of each type) and the ITI duration was 15-s. The PRBS arranged for reinforcement of correct short responses at a probability of either 0.75 or 0.25 across different sessions. The probability of reinforcement of correct long responses was the compliment of the above probabilities. Immediately following the 31-sessions under the first PRBS, subjects were returned to the final pretraining conditions noted above and the durations were changed to 3 and 5.5-s and the probability of reinforcement for correct responses was 0.50. The correspondence between right-left lever presses and short-long stimulus presentations remained constant. Once accuracy stabilized at these durations, subjects were again exposed to a 31-session PRBS with the same reinforcement probabilities as noted above. Three of the four subjects were exposed to a third PRBS presentation (J88 died shortly after completion of the second PRBS). Subjects J85 and J86 were exposed a PRBS under 2 and 8–s stimulus durations, and J88 was a PRBS under 3 and 5.5-s stimulus durations.

RESULTS

First, to demonstrate that the different stimulus conditions produced different levels of accuracy, Figure 2.2 shows accuracy expressed as log *D* (Davison & Tustin, 1978). To display discrimination performance for each condition simultaneously, the data plotted in Figure 2.2 are from the final five sessions at each relative reinforcer probability for each PRBS condition. Discrimination accuracy (log D) is plotted as a function of the logarithm of the reinforcer frequency ratio of the session from which the measure is calculated. This measure is calculated as:

$$\log D = 0.5 \cdot \log\left(\frac{B_{11}}{B_{12}} \cdot \frac{B_{22}}{B_{21}}\right) \qquad (2.3)$$

where B_{ij} refers to the frequency of response in the different cells of the matrix of Figure 2.1. This measure of discrimination performance is the geometric mean of the logarithm (base 10) of the ratio of correct to error responses and indicates the overall tendency for a subject to make a correct response independent of any response bias (Davison & Tustin, 1978). Figure 2.2 indeed shows that the different pairs of temporal durations produced changes in the propensity to make a correct response (supporting Hypothesis 1). Note that log D is not plotted for sessions where subjects made zero errors (this occurred in two sessions one subject, J85, following presentation of the 2-s stimulus).

Overall, changes in relative reinforcer probability for correct responses arranged according to the PRBS produced between session changes in response bias, log *B* (Davison & Tustin, 1978). Figure 2.3 shows response bias plotted as a function of PRBS sessions completed by each subject. Bias (log *B*) is calculated as:

$$\log B = 0.5 \cdot \log\left(\frac{B_{11}}{B_{12}} \cdot \frac{B_{21}}{B_{22}}\right) \tag{2.4}$$

were B_{ij} refers to the frequency of response in the different cells of the matrix of Figure 2.1. This measure of bias is the geometric mean of the logarithm (base 10) of the ratio of right and left responses and indicates the overall tendency for a subject to make a right (B_1) or left (B_2) lever press (Davison & Tustin, 1978). Each data point in Figure 2.3 represents performance in a single session. Inspection of Figure 2.3 reveals that bias tracked changes in the reinforcer frequency (supporting Hypothesis 2). Individual differences in performance are also readily apparent. One rat, J85, showed an overall tendency to respond more on the right lever (B_1) regardless of the relative frequency of reinforcement or stimulus conditions. The performance of rat J86 showed greater control by the changing reinforcer ratios that of the other subjects. Levels of response bias as measured by log *B* for subjects J87 and J88 were intermediate compared to that observed for the other two subjects.

Previous studies employing the PRBS design have sought to determine the extent to which performance in a given session is determined by that session's reinforcer ratio and the reinforcer ratios in previous sessions (Davison & McCarthy, 1988; Grace, Bragason, & McLean, 2003; Schofield & Davison, 1997). These analyses have been based on a generalized matching model where performance in the current session is predicted by including the current and previous sessions' reinforcer ratios. Such an analysis of the current data set requires extension of the detection model of Davison-Nevin-Alsop (Alsop, 1991; Davison; 1991; Davison & Nevin, 1999) to include previous session reinforcer ratios. The reinforcer matrix in Figure 2.1 gives the effective reinforcer terms used to predict detection performance according to the model. The notation used to describe the effective reinforcer frequency in each cell of the matrix is R'_{ij}, where *ij* corresponds to the cells of the 2x2 matrix. The present analysis extended the model by using the current and previous three sessions' reinforcer ratios to predict current session performance, as previous studies have shown little effect of greater lags (Grace, Bragason, & McLean, 2003; Kyonka & Grace, 2008; Schofield & Davison, 1997). We employed perhaps the simplest extension of the model, assuming an additive effect of current and previous sessions' effective log reinforcer ratios on current session performance (see also Davison & Baum, 2207). This model may be written:

$$\log\left(\frac{B_{i1}}{B_{i2}}\right) = \log\left(\frac{R'_{i1n}}{R'_{i2n}}\right) + \log\left(\frac{R'_{i1(n-1)}}{R'_{i2(n-1)}}\right) + \log\left(\frac{R'_{i1(n-2)}}{R'_{i2(n-2)}}\right) + \log\left(\frac{R'_{i1(n-3)}}{R'_{i2(n-3)}}\right) + \log c \qquad (2.5)$$

where B_{i1}, B_{i2}, R'_{i1}, and R'_{i2} refer to the right and left response frequencies and effective reinforcer frequencies following S_1 and S_2 presentations, respectively. Reinforcer frequencies are subscripted by *n* for the current session, *n-1* for the previous session, and so on. In Equation 2.5 the parameter log *c* represents a constant bias towards one response that is independent of changes in the reinforcer frequency ratio. Equation 2.5 was applied to the data from the fourth session on of each PRBS presentation. Each fit required one d_s parameter, one log *c* parameter, and four $d_{r(n-i)}$ parameters measuring the contribution of each past sessions' reinforcer ratios (*n* = 0-4) to current session performance. Equation 2.5 was fit to the log response ratios following each stimulus (S_1 and S_2) simultaneously by nonlinear least squares regression using the Solver tool in Microsoft Excel$^{©}$.

Figure 2.4 shows contingency discriminability (d_r) estimates for each session lag and each PRBS presentation obtained from fits of Equation 2.5. In general, Equation 2.5 provided an excellent description of the data, on average accounting for 93% of the variance (all %VAC > 0.87) in the log response ratios across subjects and conditions. Contingency discriminability for the current session (lag 0) reinforcer ratio was highest and previous session reinforcer ratios had little effect on performance. For all subjects contingency discriminability was higher when stimulus discriminability was highest (disconfirming Hypothesis 4). That is, behavior came under greater control of the current session reinforcer frequency ratio when discrimination accuracy was higher (Fig. 2.2). When subjects J85 and J86 were returned to the easier discrimination (2:8-s stimulus presentations), lag 0 contingency discriminability increased to similar, albeit lower levels than the first PRBS presentation. For subject J87 the PRBS replication of the easier discrimination (3:5-s stimulus presentations) produced slightly higher estimates of lag 0 contingency discriminability.

Although the previous analysis showed that behavior in a given session was largely under control of the current session reinforcer ratio, it is likely that the previous sessions' reinforcer ratio has some effect at the beginning of the current session. Therefore, I sought to assess control over current session performance by current and past reinforcer ratios by estimating values of contingency discriminability (d_r) within an experimental session as a function of the current and previous sessions' reinforcer ratios. Therefore, an analysis similar to the session-aggregate lag contingency discriminability analyses were performed, however for the within-session analyses log response ratios were calculated over 5 30-trial blocks. Regressions were then carried out using the current and immediately prior sessions' programmed reinforcer ratio to predict performance in each fifth of the current session (see, Davison & Baum, 2000; Grace, Bragason, & McLean, 2003). Equations similar to Equation 2.6 were fit simultaneously to log behavior ratios following S_1 and S_2, respectively for each session fifth using the programmed reinforcer ratio from the previous and current sessions. Data from each session of the first and second PRBS were used to estimate the model parameters. Each fit required a fixed d_s and log c parameter and a contingency discriminability ($d_{r(n)}$ and $d_{r(n-1)}$) parameter estimated for each block, representing the within session adjustment to the current reinforcer ratio. The results of the within session changes in contingency discriminability are displayed for the first and second PRBS exposures separately in Figures 2.5 and 2.6.

Figure 2.5 shows that in the first PRBS, where the S_1-S_2 difference was greater, control by the current session reinforcer ratio was acquired rapidly with little discernable effect by the previous sessions' reinforcer ratio (supporting Hypothesis 3).. Figure 2.5 shows that there was little effect of the previous sessions' reinforcer ratio, as assessed by d_r values of approximately 1.0, the minimum value of this parameter. Furthermore, some control by the current session reinforcer ratio was apparent within the first session fifth for 3 of 4 subjects (J87, being the exception) as evidenced by d_r values above 1.0. Estimates of contingency discriminability continued to increase throughout the session and appeared to stabilize for each subject about midway through the session. Finally, the regression fits from which the d_r estimates in Figure 2.5 are based were quite good (all VAC > 0.90).

Figure 2.6 shows the results of the within session analyses for the second PRBS in which the sample stimuli were 3 and 5.5-s, producing a less accurate discrimination (Figure 2.2) than in the first PRBS. Overall, the regressions carried out on the data from the second PRBS, resulted in relatively low percentages of variance accounted for across subjects (mean VAC = 0.66). The deviations from predicted response ratios, however, were small (mean MSE = 0.02) and unsystematic. Regressions conducted on the obtained versus predicted data from each subject gave slopes and y-intercepts not appreciably different from 1.0 and 0, respectively. Inspection of Figure 2.6 shows that estimates of within-session contingency discriminability were much lower in the second PRBS, where the difference in sample stimulus duration was only 2.5 seconds (see Figs. 2.3-2.4). More notable though was the finding that for each subject the estimates of contingency discriminability for the previous session remained above 1.0 throughout most of the session for most of the subjects. Furthermore, control by the previous sessions' reinforcer ratio was sometimes greater than that of the current session by the end of a session (partially disconfirming Hypothesis 3). This relationship is especially apparent in the parameter estimates obtained from J85. For this subject, control over response allocation seemingly switched approximately midway through a session from the current to previous sessions' reinforcer ratio, often producing indifference between the response alternatives (Fig. 2.3).

DISCUSSION

In the present study, the pseudorandom binary sequence method of varying relative reinforcer frequency was extended to a signal detection procedure. The findings presented here demonstrate that response bias (log *B*) in a signal detection task can change rapidly when the relative frequency of reinforcement changes between sessions. An extended form of the DNA detection model provided an accurate description of the effects of current and previous session reinforcer ratios on current session performance. In the first PRBS presentation, under large differences in the temporal durations defining S_1 and S_2, bias changed rapidly between sessions. Contingency discriminability was greatest at lag 0 and was largely unaffected by previous session reinforcer ratios. In the second PRBS presentation the S_1 and S_2 stimulus durations were changed such that accuracy, measured as log *D*, decreased (Figure 2.2). Under lower levels of discrimination accuracy, variation of the reinforcer ratio had a smaller effect on bias. Contingency discriminability was higher at lag 0 reinforcer ratios however, relative to reinforcer ratios in previous sessions. Estimates of contingency discriminability changed however, as the discrimination was made more difficult (Fig. 2.4). It is unclear why contingency discriminability decreased in the second PRBS exposure when accuracy decreased.

The more typical finding in studies of detection performance is that contingency discriminability is either constant or increases when stimulus discriminability decreases (for a review see Alsop & Porritt, 2006). It might be argued that the decrease in contingency discriminability seen here is the result of the use of a PRBS procedure to vary relative reinforcer frequency per se. However, at least two arguments can be made against this conclusion. First, previous studies that have varied relative reinforcer frequency or immediacy in concurrent and concurrent-chained schedules have typically shown an increased sensitivity to the conditions of reinforcement with increasing exposure to the PRBS (Grace, Bragason, & McLean, 2003; Grace & McLean, 2006; Kyonka & Grace, 2007; Schofield & Davison, 1997).

Second, at least one study that we are aware of has shown a similar effect on bias under similar procedures. McCarthy and Davison (1980) conducted a study similar to the present one in which stimulus presentations of different durations served as samples in a 2-stimulus, 2-response detection procedure. McCarthy and Davison varied the reinforcer ratio for correct responses across two levels of stimulus duration difference across several conditions with pigeons serving as subjects. In their first set of conditions, a 5-second illumination of the center key served as S_1 and a 30-second center key illumination served as S_2. In their second set of conditions, S_1 and S_2 were 20- and 30-second center key light presentations, respectively. As expected, discrimination accuracy was higher in the first condition, however for some subjects; sensitivity to reinforcement, as estimated from the Davison & Tustin, (1978) detection model, was also higher in this condition. Such a result would be consistent with the present findings; however, McCarthy and Davison (1980) reported that any apparent changes were not statistically significant according to a Sign test. However, McCarthy and Davison (1980) analyzed their data according to a detection model based on the generalized matching law and a more direct comparison of the results of their study with the current findings might be achieved be a reanalysis of their data according to the DNA model (i.e., Fig. 2.1).

Figure 2.7 presents parameter estimates from the present study and a reanalysis of McCarthy and Davison's (1980) data fit by the DNA detection model. In Figure 2.7, estimates of stimulus discriminability (d_s) are plotted as a function of estimates of contingency discriminability (d_s) from both studies. It is apparent that the results of the present study are consistent with the findings of McCarthy and Davison (1980) employing a similar detection task. Furthermore, the data from both studies suggest a degree of generality in these findings in that the studies differed in the procedure used to vary relative frequency of reinforcement and species of subject.

The present findings suggest that the PRBS method of varying relative reinforcement variables may be extended to signal detection tasks. Whether these findings hold for more complex detection procedures (Davison & McCarthy, 1989) and other stimulus dimensions will be informed by future research. However, in a research area of that has seen a large degree of quantification (Davison, 1991; Davison & Nevin, 1999), procedures that produce high quality data and rapid determination of parameter estimates are needed. Furthermore, recent research employing procedures in which contingencies change randomly have shed some light on some of the local processes governing simple concurrent choice (Krägeloh, Davison, & Elliffe, 2005). Perhaps with the further procedural development, similar advances can be made in the study of signal detection.

CHAPTER 3

RAPID SHIFTS IN THE PSYCHOMETRIC FUNCTION FOR TIME

In recent years, a considerable body of literature on the performance of non-human animals in signal detection and conditional discrimination procedures has emerged (for reviews see Davison & McCarthy, 1988; Davison & Nevin, 1999; Nevin, Davison, & Shahan, 2005). A number of studies have employed tasks in which only two stimuli are presented in a given experimental session (McCarthy & Davison, 1979; 1980b; Nevin, Olson, Mandell, & Yarensky, 1975). Although the 2-stimulus, 2-response detection procedure has been employed more frequently and has served to guide theoretical development (Alsop & Davison, 1991; McCarthy & Davison, 1984), far fewer studies have been reported in which several stimuli are presented within a single session.

In a standard 2-stimulus, 2-response detection task, subjects are presented with one of the two possible stimuli (S_1 or S_2) on each trial. One type of response (a B_1 response, e.g., a right lever press) is deemed correct and intermittently reinforced on S_1 trials and the other type of response (a B_2 response, e.g., a left lever press) is deemed correct and intermittently reinforced on S_2 trials. In the *n*-stimulus, 2-response detection task, subjects are presented with one of *n* possible stimuli on each trial. With only two responses available to the subject, each response (B_1 or B_2) is correct and intermittently reinforced following presentation of more than one stimulus. Thus, the *n*-stimulus, 2-response detection procedure involves a many-to-one mapping between stimulus classes and responses.

Davison (1991) provided a model to describe performance in *n*-stimulus, *m*-response detection procedures (see also Davison & McCarthy, 1989). The model offered by Davison (1991) was an extension of an earlier contingency discriminability model for concurrent schedule performance (Davison & Jenkins, 1985) and in the 2-stimulus, 2-response procedure is the same model proposed by Alsop (1991). The model for a 4-stimulus, 2-response detection procedure is outlined in Figure 3.1. As suggested by Davison (1991) the model assumes that in a signal detection task, reinforcers delivered for a correct response in the presence of one stimulus generalize to other stimulus-response pairs to the extent that they are similar to one another. In Figure 3.1, d_{sij} and d_{rij} represent the inverse of generalization (i.e. discriminability) between the stimulus-response and response-reinforcer pairs, respectively.

Davison and Nevin (1999) expanded upon the quantitative model of detection introduced by Alsop (1991) and Davison (1991) (DNA model hereafter) and detailed a theory of *effective* reinforcement. Effective reinforcement, in Davison and Nevin's (1999) account is an intervening variable (analogous to the subjective or discounted value of a reinforcer) representing the sum of direct and generalized reinforcement for a particular response class. Their theory proposes that response allocation in signal detection and related procedures strictly matches the effective reinforcer ratio. Thus, Davison and Nevin's (1999) theory is a matching law (Baum & Rachlin, 1969; Killeen, 1972; Rachlin, 1971), where the transformation of various reinforcer dimensions are assumed to result from imperfect discriminative control on one or more dimensions of the concurrent three-term contingencies under investigation.

Davison and McCarthy (1989) conducted the most extensive evaluation of Davison's (1991) model that has been reported to date. In the major portion of their study, pigeons were presented one of eight different wavelengths of light (measured in nanometers, nm) on each trial. Responses to the left key (B_1) were intermittently reinforced following a wavelength of 574 nm or less (559, 564, 569, 574 nm) and right responses (B_2) were intermittently reinforced after stimulus presentations of 579 nm or greater (579, 584, 589, 594 nm). Across several conditions, the relative frequency of reinforcement for correct responses following a shorter wavelength was varied from 0.1-0.9. Davison and McCarthy (1989) reported that the logarithm of the left/right response ratio (B_1/B_2) plotted as function of wavelength was an ogive, the functional form typically observed in psychophysical studies. Furthermore, the horizontal ordering of the curves depended on the relative frequency of reinforcement such that subjects demonstrated an overall bias to report the stimulus with the higher relative reinforcer frequency. Davison and McCarthy (1989) reported that Davison's (1991) model provided an excellent description of their data. Moreover, the model provided estimates of stimulus discriminability (d_{sij}) for adjacent wavelengths that were in approximate agreement with previous work on the pigeon's sensitivity to wavelength (Wright & Cumming, 1971).

While the literature on performance in simple 2x2 detection procedures continues to expand (Davison & Nevin, 1999) and extensions of models for performance in such procedures have shown some promise in more complex situations (Nevin, Davison, Odum, and Shahan, 2007), little is currently known about detection performance in transition. An important question concerns the temporal scale at which stimulus and contingency discriminability operates in order to produce an effective reinforcer value for each response alternative. Davison and Nevin suggested that their account is sequential and dynamic, implying that effective reinforcement is determined at a local level. Therefore, their theory suggests a renewed research emphasis concerned with characterizing detection performance in transition.

Recently, several investigators have employed a design to investigate choice in which the relative rates, delays, or magnitudes of reinforcement change from session to session. Hunter and Davison (1985) adapted a systems identification technique from engineering to present stochastic changes in input, in this case relative reinforcer frequency, to pigeons responding for food in a concurrent schedule of reinforcement. This procedure, called a pseudorandom binary sequence (PRBS), consists of presenting one of two reinforcer rate ratios each session. The sequence of reinforcer ratios is random, thus a current session's reinforcer ratio cannot be predicted from that of the previous session. Hunter and Davison's (1985) analysis showed that pigeons' relative response rates adapted to abrupt changes in the reinforcer rate ratio in approximately five sessions, although the pigeons were less sensitive to these changes than in more typical steady-state experimental designs.

The findings of Hunter and Davison (1985), as well as several others to follow (Mazur, 1992, 1995, 1997; Schofield & Davison, 1997), are somewhat surprising in light of most research on choice (see Davison & McCarthy, 1988). That is, the use of traditional steady-state designs, in which a single reinforcer rate ratio is in effect for many sessions (20-30) until preference is relatively stable, seems to suggest that behavior in several choice paradigms is slow to change. Numerous studies, employing what may be considered as variations on the PRBS design have shown that choice adapts rapidly to frequent changes in outcomes (Davison & Baum, 2000, 2002, 2003; Gallistel, Mark, King, & Latham, 2001; Landon, Davison, & Elliffe, 2003)

Some recent work employing the PRBS design or other means of producing frequent changes in reinforcer parameters, has shown that preference not only adapts rapidly to abrupt changes in relative rates of primary reinforcement, but also to changes in conditioned reinforcement value (Grace, 2002; Grace, Bragason, & McLean, 2003; Mazur 2002; Mazur, Blake, & McManus, 2001). The concurrent chains procedure involves a choice period or initial link in which repeated choices are made between two options. Occasionally, choice of one option produces an outcome period or terminal link, signaled by a change in stimulus conditions, in which further responding leads to the availability of food. Responding in the choice or initial link phase is usually assumed to be maintained by conditioned reinforcing value of access to the terminal link stimuli (Fantino, 1969; 1977; Herrnstein, 1964; Mazur, 2001). These studies have manipulated the value of terminal link stimuli in concurrent chains procedures by varying the frequency of encountering the stimuli and by varying the delays to primary reinforcement in the presence of the terminal link stimuli.

Grace, Bragason, and McLean (2003) showed that pigeons' response allocation, measured, as relative response rate in the initial links of a concurrent chain, is sensitive to changes made to primary reinforcement delays in the terminal links according to a 31-session PRBS. In their Experiment 1, Grace and colleagues held the delay to primary reinforcement constant in one terminal link (8-s), while the delay to reinforcement in the other terminal link varied from session to session between two values (4- or 16-s). After the first 31-sessions of exposure, the pigeon's sensitivity to the relative terminal link delays to reinforcement was largely under control of the current sessions' relative delays. Grace and colleagues exposed their pigeons to the PRBS twice more and showed that control by current session reinforcement conditions continued to increase for all four subjects. Subsequent analyses, from the third PRBS, showed that the birds' preference adapted to the current session reinforcer delay ratio within approximately one third of the session or 24 choice cycles. In their Experiment 2, Grace et al. held the delay to reinforcement in one terminal link constant (8-s) while varying the other delay each session between 2-s and 32-s. Thus, according to this arrangement the delay to reinforcement for one alternative is sampled from a potentially infinite population each session. Grace et al. showed that under these conditions, pigeons' choices adapted to the session-to-session changes in delays to reinforcement in a very similar manner to the delays in their Experiment 1.

Following Grace et al (2003, see also Grace & McLean, 2006; Kyonka & Grace, 2007), Kyonka and Grace (2008) presented data, again on pigeons' choices in concurrent chains schedules, under more complex variations in reinforcer parameters according to the PRBS design. In their Experiment 1, Kyonka and Grace employed a concurrent chains procedure in which the relative delays and magnitudes of reinforcement in the terminal links varied from session to session each according to a separate PRBS. Kyonka and Grace's findings were entirely consistent with their previous work in that pigeons' choices adapted rapidly each session to both dimensions of reinforcement. Kyonka and Grace's data supported the assumption that reinforcer rate and magnitude ratios have independent effects on choice. Additionally, these results are consistent with published findings obtained from more traditional designs previously employed to test the assumption of the generalized matching law (Killeen, 1972; Rachlin, 1971) that different dimensions of reinforcement combine independently to determine reinforcer value.

The studies reviewed here provide support for the use of designs employing dynamic changes in reinforcer parameters to investigate choice behavior in transition. However, no such studies employing a PRBS design to investigate choice in a signal detection procedure have been published. The present study sought to extend the PRBS design to a 5-stimulus, 2-response signal detection procedure to determine the extent to which response bias following a particular stimulus develops within a single experimental session. The experiment reported here provides both an extension of the PRBS design to signal detection and conditional discrimination procedures, as well as a much-needed systematic replication of Davison and McCarthy (1989). Furthermore, we sought to extend Davison's (1991; see also Davison & Nevin, 1999) *n*-stimulus model of detection to quantify the extent of carryover from previous sessions' reinforcer ratios on current session response ratios. In addition, one of the sample stimuli presented each session was never followed by food presentation regardless of which response was made; analogous to a maintained generalization procedure (Blough, 1969). I asked whether performance following this stimulus (technically an S^{Δ}) was similarly biased towards the higher reinforcer probability response alternative as was responding that actually produced reinforcer deliveries. If so, this would provide some support for Davison and Nevin's (1999) notion of effective reinforcement.

Hypotheses

1) By the end of the first PRTS, the current session response bias, assessed by lag d_r, will be primarily under control of the current session reinforcer ratio. Contingency discriminability at lag 0 will increase across PRTS presentations.
2) Within experimental sessions, bias will gradually shift from control by the previous sessions' to the current sessions' reinforcer ratio.
3) The response ratio following presentation of S_3 will be biased towards the response alternative correlated with the higher probability of reinforcement.
4) Modeling within-session adjustment to the current session reinforcer ratio by changes in contingency discriminability will produce orderly shifts in the psychometric function according to the programmed relative reinforcer probabilities.

METHOD

Subjects

The subjects were three female Long Evans Hooded rats J93, J94, and J99. Rats J94 and J99 had prior exposure to a free-operant temporal discrimination procedure. Food deprivation was held constant for each subject by post-session feeding (12g). The rats were housed individually and had free access to water when in their home cages in a vivarium with a 12:12 hr light/dark cycle (lights on at 6:00

a.m.). Sessions were conducted daily, at approximately the same time with few exceptions. Experimental sessions were conducted during the rats' light period.

Apparatus

Same as the second chamber described in Experiment 1.

Procedure

Preliminary Training. Prior to discrimination training, J94 and J99 were placed on a concurrent random-ratio (RR), RR schedule of reinforcement. For rat J93, lever pressing was shaped by the method of successive approximation and then placed on the concurrent RR, RR schedule. Throughout this preliminary lever-press training, reinforcers were programmed for each response according to a dependent schedule (Stubbs & Pliskoff, 1969) such that in the event that a reinforcer was assigned to one response alternative, no other reinforcer could be assigned until the previously allocated reinforcer was obtained by the subject. Subjects were exposed to this procedure for approximately four weeks and the ratio requirements for both levers were increased to a terminal value of RR 3.

Subsequently, each subject was exposed to the basic temporal discrimination procedure. On each trial, the houselight was illuminated for one of five durations (2, 3.5, 4.5, 5.5, or 8-s). Following the sample stimulus presentation, both lever lights were illuminated and responses to the right lever were reinforced following sample durations of 2 and 3.5-s and responses to the left lever were reinforced following sample durations of 5.5 and 8-s. Left and right lever presses following a 4.5-s sample presentation were never reinforced. Initially, each correct response was followed by two, 2-s presentations of the dipper, with a 0.5-s delay between the presentations.

Incorrect responses led directly to the intertrial interval (ITI) in which all lights in the chamber were extinguished for 7-s. Each session consisted of 200 trials, with 40 presentations of each sample. Following approximately 30 sessions for each subject, the overall density of reinforcement was decreased by implementing a dependent schedule of reinforcement. The dependent schedule or controlled reinforcer ratio procedure (McCarthy & Davison, 1984) ensured an approximately equal number of reinforcers were obtained for responding to both correct response alternatives. No attempt to equate the number of reinforcers within a stimulus class (2.0-3.5 and 5.5-8.0-s) was made. Upon transition to the dependent schedule correct responses that were not eligible for reinforcement had the same consequences as error responses (7-s ITI) and correct responses that were eligible for reinforcement continued to produce 4-s of access to the dipper followed by a 2.5-s blackout. This training phase continued for each subject until the percentage of correct responses following each stimulus was deemed stable by visual inspection of the data. For rats J94 and J99 training was deemed complete after 45 sessions and for J93 after 80 sessions.

Upon completion of training on the dependent schedule phase, each subject was exposed to a procedure in which the relative probabilities of reinforcement changed each session. The relative probability of reinforcement for correct responses following one of the shorter stimulus durations was 0.25, 0.5, or 0.75. This is in effect a pseudorandom ternary sequence (PRTS). The sequence lasted for a total of 36 sessions; each reinforcer probability was allowed to occur three times in each block of nine sessions. The order of reinforcer probability session was determined separately for each of the four blocks of nine sessions according to the random number generator tool in Microsoft© Excel. Figure 3.2 illustrates one 36 session PRTS, where the logarithm (base 10) of the programmed relative reinforcer frequency ratio (R_R/R_L) is plotted according to session.

Each subject was exposed to the 36-session PRTS three times.

RESULTS

As in Experiment 1 and previous studies employing the pseudorandom sequence design (cf. Schofield & Davison, 1997), it is important to quantify the extent of control by the present and past reinforcer frequency ratios on current session performance. The data from Experiment 2 can be fit by Equation 2.5, but require the addition of a stimulus discriminability (d_{sij}) estimate for each pair of sample stimuli. Following Davison and Nevin (1999), we fit Equation 2.5 to the present data with four stimulus discriminability parameters for each adjacent pair of stimuli: d_{s12}, d_{s23}, d_{s34}, and d_{s45}. Estimates of d_{sij} for all other combinations of stimuli were obtained by multiplying the above estimates, so that for example, d_{s14} is the product of d_{s12}, d_{s23}, and d_{s34} (see also, Davison & Nevin, 1999; Krägeloh, Elliffe, & Davison, 2006). A matrix of the summed reinforcer frequencies divided by the appropriate discriminability parameters were created for each session giving the effective reinforcer frequency for each response alternative. The logarithm of the ratio of the effective reinforcer frequencies was used to predict log response ratios following each stimulus. For example, following sample S_3, the effective reinforcer frequency for each response is:

$$R'_{31} = \frac{R_{11}}{d_{s13}} + \frac{R_{21}}{d_{s23}} + \frac{R_{42}}{d_{s34}d_{r12}} + \frac{R_{52}}{d_{s35}d_{r12}} \tag{3.1}$$

and

$$R'_{32} = \frac{R_{11}}{d_{s13}d_{r12}} + \frac{R_{21}}{d_{s23}d_{r12}} + \frac{R_{42}}{d_{s34}} + \frac{R_{52}}{d_{s35}} \tag{3.2}$$

The log effective reinforcer ratio (R'_{31}/R'_{32}) obtained in the current and previous three sessions were used to predict the response ratio following each stimulus in each session of the three PRTS exposures. The effect of each sessions' effective reinforcer ratio on current session response ratios were assumed to additive as in Experiment 1. Therefore, fits of Equation 2.5 to the data of Experiment 2 required that four stimulus discriminability parameters, an inherent bias term (log *c*), and four contingency discriminability parameters be estimated.

Figure 3.2 shows lag contingency discriminability estimates obtained from fits of Equation 2.6 for each rat and PRTS. Overall, contingency discriminability was highest at lag 0 and near 1.0 at greater lags. Between the first and second PRTS presentations the effects of previous sessions' reinforcer ratios decreased for each subject. For J94 and J99, lag 0 contingency discriminability increased from the first and second PRTS exposures and then decreased on the final PRTS to levels similar to the first exposure. For J93, little change in lag 0 contingency discriminability occurred between the first two PRTS exposures, however, lag 0 contingency discriminability increased to high levels on the third PRTS exposure for this subject. Therefore, the data from Experiment 2 conform to previous studies (supporting Hypothesis 1) employing the PRBS design showing that the extent of control by the current session reinforcer ratio primarily occurs in the first two exposures (Schofield & Davison, 1997; Grace, Bragason, & McLean, 2003).

To examine within-session changes in contingency discriminability as in Experiment 1, the data from each session of the third PRTS exposure of Experiment 2 were divided in fifths (or 8 presentations of each stimulus). Because aggregating the data in this way may frequently lead to exclusive preference for a response alternative, we fit a proportional version of the DNA model to the session fifth data (see Davison & McCarthy, 1989). These fits require that several parameters be estimated for each session fifth: four stimulus discriminability parameters (d_{sij}), an inherent bias term (log c), and a contingency discriminability parameter ($d_{\mathrm{r(n\text{-}i)}}$) measuring the effect of reinforcer frequency ratios from the current and previous session. The stimulus discriminability and inherent bias terms were, however, constrained to have the same value for each session fifth as variables affecting these parameters were held constant. A contingency discriminability term was estimated for the current and previous sessions' reinforcer ratio at each session block, totaling ten contingency discriminability free parameters. An effective reinforcer frequency was obtained for each response alternative and session fifth as in Equations 3.1 and 3.2 above. The effective reinforcer frequencies from the current and previous session were multiplied to give an overall effective reinforcer term. Therefore, using Equations 3.1 and 3.2 to obtain effective reinforcer frequencies for each response following each stimulus, the effective reinforcer terms for the current and previous sessions were concatenated:

$$R''_{ij} = \prod_{i=0}^{2} R'_{ij(n-i)} \tag{3.3}$$

where R''_{ij} is the overall effective reinforcer frequency including any effect of past reinforcers, then used to predict relative response frequency following each stimulus

$$\left(\frac{B_{i1}}{B_{i1}+B_{i2}}\right) = \left(\frac{cR''_{i1}}{cR''_{i1}+R''_{i2}}\right) \tag{3.4}$$

were *c* is again an overall bias towards a response alternative. Equation 3.4 therefore assumes that response allocation strictly matches the relative effective reinforcer frequency, which is a function of current and past contingencies of reinforcement. This model was fit to individual subject data so as to minimize the sum of squared error between the obtained and predicted response proportions of all stimulus presentations and within session blocks.

Figure 3.4 shows the within session changes in contingency discriminability for each subject from the third PRTS exposure. An effect of the previous sessions' reinforcer ratio is evident in the first block of trials for each subject. The influence of previous sessions' reinforcer ratios decreased gradually across the session (supporting Hypothesis 2). For each subject, lag 0 contingency discriminability increased in a nearly monotonic fashion within the session and approaches asymptotic levels in the final two blocks of trials. Therefore, Figure 3.4 demonstrates that response allocation moves from near indifference to relatively stable preference for the higher reinforcer frequency alternative about midway through a session or following approximately twenty presentations of each stimulus. As in Experiment 1, the model used to assess within-session changes in contingency discriminability provided an adequate fit to the session fifth data. The average percentage of variance accounted for was modest (mean VAC = 73%), however, regressions performed on obtained versus predicted performance revealed no systematic deviations.

Figure 3.5 shows psychometric functions obtained for each subject from the present experiment. The data were taken from the last two session-fifths (see Fig. 3.4) of the final PRTS because performance had reached a steady state by this point within an experimental session. The proportion of “long” or left responses following each sample stimulus were averaged across sessions and grouped according to programmed reinforcer ratio (Fig. 3.2). Figure 3.5 shows that the proportion of responses to the left lever, indicating a long classification, increased as an ogival function of the preceding sample stimulus duration. Furthermore, each psychometric function shifted along the x-axis according to the programmed reinforcer ratio (supporting Hypothesis 4). Therefore, Figure 3.5 affirms that the data obtained from the present method of varying reinforcer frequency produces reliable psychometric functions and the shift in each curve produced by varying the relative frequency of reinforcement for correct responses is similar to that observed in traditional steady-state procedures (Bizo & White, 1995; Davison & McCarthy, 1989).

As a further check on the adequacy of the extension of the DNA model proposed here to model within-session adjustments to a frequently varying reinforcer ratio we assessed the model’s ability to fit the psychometric data in Figure 3.5. Keeping in mind that the extended DNA model of Equations 3.3 and 3.4 were fit to all the data of the third PRTS from each block of 40 trials gave 900 data points per subject. The models’ predictions for the last two blocks of trials (trials 161-200) were averaged in the same manner as the obtained data (Fig. 3.5). Table 3.1 gives the parameters of the DNA model along with goodness of fit indices for the data from blocks four and five. The fits of the DNA model incorporating carryover from the previous session’s reinforcer ratio were excellent. Furthermore, the assumption of constant stimulus discriminabilities and an increasing contingency discriminability, and thus increasing bias towards the higher reinforcer frequency alternative, provided an accurate description of the individual subject data.

Finally, a measure of response allocation following each sample stimulus presentation was sought that characterizes the changing response allocations as a function of the opportunity to observe them. Cumulative response proportion was chose as a measure of preference because this measure naturally smoothes the data (for discussion see Gallistel et al, 2007). Data from the third PRTS were used for theses analyses and response totals were summed across each session by order of stimulus presentation. Therefore, cumulative relative response frequency is plotted as a function of successive presentations of a particular sample stimulus.

The cumulative proportions of B_1 choices (p) for each subject have been converted to a logit p (logit $p = \log(p/(1-p))$) and are plotted in Figures 3.6-3.8. The cumulative choice proportion plots in Figures 3.6-3.8 show changes in preference within experimental sessions that were similar to those reported in other studies employing similar procedures (Krägeloh & Davison, 2003; Krägeloh, Elliffe, & Davison, 2006). Figures 3.6-3.8 shows that a preference for the higher reinforcer frequency alternative typically emerged within five to ten presentations of a sample stimulus duration. A relatively large degree of variability in response allocation in the first few trials is evident for each subject as expected. Recall that responding following S_3 never produced a food presentation throughout the experiment yet choice is governed by the overall reinforcer frequency ratio. The cumulative choice proportions, therefore suggest a fairly rapid local process by which effective reinforcer allocation operates on response allocation (supporting Hypothesis 3).

DISCUSSION

In the current experiment, bias changed rapidly when the reinforcer frequency ratio for correct choices changed between sessions. An extension of the DNA model that incorporated the effects of current and previous sessions' effective reinforcer ratios provided a good description of both aggregate and within-session changes in response bias. Control by the current sessions' reinforcer ratio generally increased with increasing exposure to the PRTS, particularly with respect to effects of previous sessions' reinforcer ratios decreasing between the first and second exposures. Within-session adjustment to the current session reinforcer ratio was most rapid between the first and second session fifths (Fig. 3.4).

The session-aggregate lag contingency discriminability estimates portrayed in Figure 3.3 are consistent with previous data obtained from the pseudorandom sequence method of varying relative reinforcer frequency in a simple detection task and in simple concurrent and concurrent chained schedules of reinforcement (Experiment 1; Schofield & Davison, 1997; Grace, Bragason, & McLean, 2003; Grace & McLean, 2006; Kyonka & Grace, 2008). The model employed here assumed an additive effect of previous sessions' reinforcer ratios, which is consistent with previous modeling; however all previous studies have employed a generalized matching law analysis of carryover effects in the pseudorandom sequence procedure (Davison & Hunter, 1979; Davison & McCarthy, 1988). The extension of the generalized matching law to account for the effects of previous sessions' reinforcer ratios was inspired by research in which multiple reinforcer dimensions (i.e., rate and magnitude) have been varied simultaneously and the assumption of an additive effect of each dimension has provided an accurate account of choice between alternatives differing on multiple reinforcer dimensions (Davison & Baum, 2003; Keller & Gollub, 1977; McLean & Blampied, 2001; but see Elliffe, Davison, & Landon, 2008). Therefore, the present use of an additive version of the DNA model may be a possible means of extending this model to multiple reinforcer dimensions (Alsop & Porritt, 2006; Davison & Nevin, 1999).

The within-session adjustments to the current session reinforcer frequency ratio were fairly rapid, occurring mostly between the first and second session fifths. The finding of rapid within-session adjustment to current reinforcer ratios is consistent with previous findings (Grace, Bragason, & McLean, 2003; Grace& McLean, 2006) and suggests that behavior is effected by both short- and long-term effects of the reinforcer ratio. The adaptation of within-session responding to current reinforcer frequency ratios was the product of two processes; an increase in control by current session contingencies and a decrease by previous session contingencies (Fig. 3.4). Therefore, at the beginning of a session, there was little or no overall bias towards a particular response alternative. That is, between sessions behavior regressed toward indifference, consistent with previous findings that in rapidly changing environments, preference reverts to levels reflecting long-term reinforcer allocations (Landon, Davison, & Elliffe, 2003). Because the present procedure employed reinforcer ratios that varied symmetrically around 1:1, the finding of approximate indifference at the beginning of an experimental session was expected.

Although the within-session changes in behavior (Fig. 3.5) are well summarized by changes in the estimates in contingency discriminability, the changes in behavior allocation displayed in Figure 3.6 highlight the speed of changes in bias and the spread of effect of the reinforcer ratio across stimuli. The cumulative preference data showed that responding following each stimulus was often biased towards the higher reinforcer frequency alternative before ten presentations. Therefore, as suggested by the DNA model, reinforcers delivered following a particular response and following one stimulus effected behavior following all other stimuli. Given that the stimuli were presented randomly, it is possible that preference for a response alternative could be observed on the first presentation of a particular stimulus. Krägeloh, Elliffe, and, Davison (2006; see also Krägeloh & Davison, 2003) reported similar effects when they varied the reinforcer ratio across several seven values within session and each reinforcer ratio was signaled by a different stimulus. The present findings and those of Krägeloh and colleagues suggest that the spread of reinforcer effects along stimulus and response dimensions can be observed at a local level and that any serious attempt to model behavior at this level will require incorporating such findings.

Finally, as discussed previously the DNA model performed well in several respects as applied to the present experiment. An extension of the model incorporating previous sessions' reinforcer ratios described both session-aggregate and within-session changes in bias (Figs. 3.3-3.4). The changes in response allocation following each sample stimulus were rapid and showed evidence of generalization across both stimulus and response dimensions, as suggested by the DNA model. Of special interest, the changes in bias following presentation of S_3 were similar to that observed following other stimuli in which responding actually produced reinforcer deliveries. Therefore, the present study provides a strong demonstration of an important assumption of the DNA model. According to the model reinforcers delivered following one stimulus or response will have an effect on behavior following all other stimuli to the extent that the stimuli or responses in question are similar to one another. The spread of reinforcer effect along stimulus and response dimensions produces an *effective* or perceived number of reinforcers that may differ from that actually delivered by the experimenter (Davison & Jenkins, 1985; Killeen, 1994). In the case of behavior following presentation of S_3, the effective allocation of reinforcers produced a preference for a response alternative when no reinforcers were ever actually delivered for either response following presentation of this stimulus. Therefore, the present results lend support to the theoretical assumption that behavior in detection procedures is determined by the effective allocation of reinforcement (Davison & Nevin, 1999). Furthermore, these findings suggest not only that a reinforcement-based theoretical approach to understanding signal detection performance may be of some value to those studying perception, but also that studying perceptual phenomena may provide important insights into the process of reinforcement itself.

CHAPTER 4

DYNAMICS OF ATTENDING IN THE REPEATED ACQUISITION OF A TEMPORAL DISCRIMINATION

The role of attending has long been recognized as an important feature in the establishment of stimulus control of operant behavior (Hull, 1950; Wyckoff, 1952, 1969). Dinsmoor (1985) pointed to the decrease in induction or transfer between stimuli correlated with reinforcement and those that are not as training progresses to be the hallmark of discrimination learning. On this view, it is the differential correlation between discriminative stimuli and the training context with reinforcement that comes to exert control over behavior in the formation of stimulus control.

Early work by Heinemann and colleagues (Heinemann, Avin, Sullivan, and Chase, 1969) showed that once asymptotic levels of performance on a sound intensity generalization task had been achieved, accuracy at the tested end points (65 and 100 dB, respectively) of the intensity continuum was less than perfect. Their generalization testing procedure entailed brief presentations of white noise followed by the availability of two response alternatives. In different experiments, responses to one key following a class of stimuli less than a critical value were reinforced and responses to the other key following a class of stimuli greater than a critical value were reinforced. Psychometric functions of the proportion of responses to the "high intensity" key as a function of intensity of white noise were obtained for each subject. Heinemann and colleagues found that the proportion of responses to the high intensity key were often greater than zero and less than one at the extreme lower (65 dB) and upper (100 dB) ends of the intensity values tested, respectively.

To account for the less than unit range of their obtained psychometric functions, Heinemann and colleagues provided a theoretical treatment based on attention. Specifically, they assumed that on some trials, their subjects' choices were controlled by unspecified stimuli other than the auditory dimension. To assess the degree to which stimuli other than auditory stimuli controlled the subjects' behavior, Heinemann and colleagues used the following equation as a correction for inattention

$$p(R|A) = \left(\frac{p(R) - p(R_l)}{p(R_u) - p(R_l)} \right) \tag{4.1}$$

where $p(R \mid A)$ is the probability of a response $p(R)$ given attention (A) to the prior stimulus. The terms $p(R_u)$ and $p(R_l)$ denote the obtained upper and lower asymptotes of the psychometric function. With this correction, Heinemann and colleagues fit normal ogives to the obtained psychometric functions and showed that the probability of attending depended on training conditions prior to generalization testing. Specifically, subjects trained on a more difficult discrimination before generalization testing gave steeper (i.e., more step like) psychometric functions than those subjects who had been trained on an easier discrimination.

Heinemann & Avin (1973) trained pigeons on a maintained generalization procedure, in which right or left key pecks following different intensities of white noise produced access to food. In their experiment 2, subjects were presented one of ten possible intensities (60-96 dB, in 4 dB steps) of white noise on each trial and were required to peck the left key given an intensity of 76 dB or less and a peck to the right key given an intensity of 80 dB or greater. Heinemann and Avin analyzed psychometric curves from separate 10 session blocks of training (100 sessions total). Applying the same asymptote correction as above (Eq. 4.1), Heinemann and Avin (1973) showed that the probability of attending to the sample stimuli increased in a negatively accelerated fashion towards 1.0 across training blocks.

Blough (1996) attempted to isolate different factors that contribute to errors in the matching-to-sample (MTS) performance of pigeons. He distinguished three separate sources of error that may occur in various stimulus control procedures. Blough’s analyses were based on fitting a normal ogive to psychometric functions, which provide an estimate of mean and standard deviation. The standard deviation or slope of the obtained psychometric curve is commonly referred to as sensitivity or d' in signal detection theory terminology (Green & Swets, 1966). The mean or point of subjective equivalence (PSE) of the psychometric curve is an estimate of response bias or the propensity to report one stimulus more frequently than the other. Finally, Blough provided estimates of the lower and upper asymptotes of the obtained psychometric functions. These different error sources are analogous to those provided by Heinemann et al (1969) with their attention-corrected ogive fits. In a series of experiments, Blough (1996) showed that some manipulations, such as sample duration and the length of a retention interval, produced independent effects on the parameters of the psychometric function.

More recently, Nevin, Davison, and Shahan (2005) provided an account of attending in conditional discriminations partly informed by the observing response literature. Their model is an extension of a previous model of signal detection and conditional discrimination (Alsop & Davison, 1991; Davison & Nevin, 1999), furthermore, the model is more general than previous attempts in that it can provide estimates of attending in the absence of obtaining a complete psychometric function. The model provided by Alsop and Davison (the DNA model) is presented in Figure 4.1. This model of detection and conditional discrimination performance assumes that reinforcers delivered for correct responses (corresponding to cells 11 and 22) generalize to the other cells via the psychometric distances between the responses and stimuli present in the task. The parameters used to estimate psychometric distances are d_r and d_s, the distance between the responses, as defined by the comparison stimuli or locations, and sample stimuli, respectively. It is important to note that these parameters are assumed to represent the physical differences among stimuli and the sensory capacities of the organism under study.

Nevin, Davison, and Shahan (2005) showed that with the addition of parameters representing the probability of attending to the sample and comparison stimuli, the model could account for previous data sets that the DNA model, which assumed perfect attending, could not. Nevin, Davison, & Shahan (2005) provided equations derived from behavioral momentum theory (Grace & Nevin, 1997; Nevin & Grace, 2000) which predict that the probability of attending is related to the rates of reinforcement correlated with the sample and comparison stimuli relative to the background reinforcer rate in the experimental context. In essence, the equations predict that higher rates of reinforcement will produce a negatively accelerated increase in rates of attending (Shahan, 2002), analogous to free-operant response rates (Catania & Reynolds, 1968; Herrnstein, 1970). Although precise prediction requires the use of the attending equations (i.e., Eq. 1.8 & 1.9), an illustration of the role of attending in the model does not require the equations, therefore, those equations will not be repeated here. The model assumes that the subject attends to the sample and the comparison stimuli with probability $p(\text{A}_s)$ and $p(\text{A}_c)$ on each trial. This process may be represented by a Markov chain as in Nevin, Davison, and Shahan's (2005) Figure 4 (presented here in Fig. 4.2). The Markov chain consists of four states corresponding to complete attention (State 1) or inattention (State 4) to the samples and comparisons, attention to the samples, but not the comparisons (State 2), and inattention to the samples, but attention to the comparisons (State 3). If the subject attends to the sample stimulus and the comparisons on a given trial (i.e., $p(\text{A}_s) = p(\text{A}_c) = 1$), then behavior is assumed to be governed by the equations presented in State 1 of Figure 4.2 (i.e., the DNA model). If the subject attends to the sample stimuli, but does not attend to the comparisons, then behavior is governed by the equations for State 2 in Figure 4.2. States 3 and 4 correspond to trials in which the subject does not attend to the sample and either attends (State 3) or does not attend (State 4) to the comparisons. Note that only in States 1 and 3, do the parameters estimating psychometric distances contribute to predicting differential responding to the comparisons. States 2 and 4 both predict that the subject responds with equal probability to either comparison. Nevin, Davison, & Shahan (2005) showed that by assuming that subjects do not attend to the samples on every trial ($p(\text{A}_s) < 1.0$; $p(\text{A}_c) = 1.0$) their model was able to account for findings that were discrepant with the DNA model. Therefore, their analysis suggests that in many conditional discrimination and signal detection procedures without a retention interval, behavior is governed by States 1 and 3 of the model as illustrated in Figure 4.2.

As mentioned above, Nevin, Davison, and Shahan’s (2005) account of attending is predicated on the functional similarity between attending in conditional discrimination procedures and behavior in observing response procedures. Research with observing response procedures (Wyckoff, 1952, 1969; Fantino, 1977) has been the empirical basis for behavior analytic accounts of attending. An extensive empirical literature (Dinsmoor, 1983) has shown that observing responses are acquired (Dinsmoor, Mueller, Martin, & Bowe, 1982; Dinsmoor et al., 1983) and maintained (Dinsmoor, Brown, & Lawrence, 1972) by the conditioned reinforcing value of stimuli (S^D) correlated with primary reinforcement. Therefore, the account of Nevin et al. suggests that the probability of a subject observing the sample and comparison stimuli in a conditional discrimination is determined by the conditioned reinforcing value (Fantino, 1969; Herrnstein, 1964, Grace, 1994; Mazur, 2001) of those stimuli. That is, the extent to which differences among the sample stimuli and comparison stimuli actually exert discriminative control over behavior exists on a continuum ranging from no control to that determined by maximal conditioned reinforcing value, limited by psychophysical differences among the stimuli.

The present research provides a systematic replication and extension of the work of Heinemann and Avin (1973). Rather than provide a single acquisition curve for each subject, however, the present work seeks to provide within subject replications by employing a successive reversal or repeated acquisition design (Boren, 1969; Thompson, 1970; 1971). Specifically, subjects will learn a temporal classification task in which stimuli from the short duration class is correctly identified by one of two responses (for example, a right response) and stimuli from the long duration class are correctly identified by the other response alternative (for example, a left response). Following a fixed number of experimental sessions, the relation between the short and long stimulus classes and the correct comparison response location is reversed. Furthermore, the present experiment sought to characterize repeated acquisition under conditions in which each correct response is reinforced with both equal and unequal probabilities.

The present experiment also provides a test of the predictions of Nevin et al.'s model of attending and perhaps may shed some light on the role of conditioned reinforcement in conditional discriminations. As discussed above, it is clear that the acquisition of a conditional discrimination may be understood as the gradual increase in control by the relevant stimulus dimension correlated with reinforcement (Heinemann & Avin, 1973). The approach of Nevin et al. provides two possible sources of control over the subjects' discrimination performance; attending to the sample and the comparison stimuli, respectively. Assuming that these processes can be dissociated, the repeated acquisition of a conditional discrimination may be inferred to result predominately from changes in the probability of attending to either the sample stimuli or the comparison stimuli as training progresses.

Research on the acquisition of preference in the concurrent-chains procedure has shown that evidence of control by primary reinforcement occurs before any preference is observed (Grace, 2001; Grace & Nevin, 1999). That is, initial link preference for the shorter terminal link delay, which is assumed to be mediated by the value of the terminal link stimuli as conditioned reinforcers, develops once subjects have already learned the delays to primary reinforcement in the respective terminal links. If conditional discrimination performance is mediated by the value of the sample and comparison stimuli, one might expect to see the development of preference among comparisons in a conditional discrimination emerge before evidence of conditional stimulus control by the samples, analogous to backward chaining. Consequently, the goal of the present study is to assess the degree of independence in the acquisition of attending to the sample and comparison stimuli by manipulating the relative value of these stimuli by varying the relative probabilities of reinforcement for correct comparison choices.

Hypotheses

1) Subjects will show rapid repeated acquisition of a temporal discrimination. Furthermore, changing the location across repeated-acquisitions of the correct response following each stimulus class will have no effect on the speed of acquisition.
2) When the probabilities of reinforcement for correct responding are unequal, biased responding will approach asymptotic levels at a rate higher than that of discrimination accuracy.
3) The attending-augmented DNA model will portray the differences in the speed of acquisition between bias and discrimination as a difference in the probabilities of attending to the sample and comparison stimuli, respectively. Specifically, attending to the comparison stimuli will increase at a rate higher than that of attending to the sample stimuli.

METHOD

Subjects

The subjects were five male Long Evans Hooded rats (J105, J106, J107, J08, and J109). All subjects were experimentally naïve at the beginning of the experiment. Food deprivation was held constant for each subject by post-session feeding (15g). The rats were housed individually and had free access to water when in their home cages in a vivarium with a 12:12 hr light/dark cycle (lights on at 6:00 a.m.). Sessions were conducted daily, at approximately the same time with few exceptions. Experimental sessions were conducted during the rats' light period.

Apparatus

Same as the first chamber described in Experiment 1.

Procedure

Preliminary Training. Initially, left and right lever pressing was established via autoshaping. Subsequently, subjects were exposed to a discrete trials procedure in which the light above either the left or the right lever was lit and a response to the appropriate lever ended the trial with a 3 second milk presentation. This training phase lasted approximately five days or until each rat was reliably pressing each lever. Next, each subject was exposed to a similar procedure although both lever lights were illuminated on each trial and reinforcers were programmed for responses to only one lever on each trial. Reinforcers were equally likely to be programmed for each alternative, and once set up for a particular response, held until that reinforcer is obtained. Thus, during this portion of training, subjects were exposed to a dependent concurrent fixed-ratio (FR) 1, FR 1. This training procedure was conducted daily for approximately twenty days for each subject.

Repeated Acquisition. After subjects were reliably responding on each lever, switching between levers within a trial, and pressing each lever with near equal frequency, they were placed on the initial temporal discrimination procedure. On each trial the houselight was illuminated and sonalert were turned on for one of six durations (2, 2.6, 3.48, 4.6, 6.1, or 8-s). Following the sample stimulus, both lever lights were illuminated and responses to one lever were reinforced following sample durations less than 4-s and responses to the other lever will be reinforced following sample durations greater than 4-s. The mapping of stimulus class to the correct response location was counter-balanced across subjects. The mapping between stimulus class and correct response locations will be denoted by whether the short or long classes of durations are correct following B_1 (right) responses, thus (S)B_1 signifies that right responses are correct following one of the short duration samples and left (B_2) responses are correct following one of the long duration samples. Subjects J105, J107, and J109 were initially assigned to (S)B_1, in which B_1 responses were deemed correct and reinforced following short durations and B_2 responses following long durations were deemed correct and reinforced. The mapping between short and long stimuli and correct response locations was the opposite [(L)B_1] for subjects J106 and J108. All correct responses produced 3-s access to milk followed by 2-s of blackout. Errors led directly to an intertrial interval (ITI) lasting 5-s during which the chamber was dark. Each sample stimulus duration was presented 42 times per session, resulting in 252 trials total per session. After 20 sessions of training, the sample-stimulus correct-response mappings were reversed for each subject. The first reversal was carried out for 20 experimental sessions.

Once each subject had been exposed to a complete reversal (i.e., both levers being correct following short (or long) durations for 20 sessions), the scheduling arrangement for correct responses was changed to a dependent schedule (Stubbs & Pliskoff, 1969). Thus, reinforcers were scheduled for each correct response with equal probability and once a reinforcer was assigned to a particular correct response, no other reinforcers could be obtained until that particular correct response was made.

Two subjects J105 and J106 required several more sessions than the others to learn the initial discriminations. These subjects also demonstrated took considerably longer to relearn the discriminations after reversals. Subsequently these subjects were trained using a procedure in which all correct responses resulted in feedback (brief-paired stimulus presentations). After multiple reversals with a correction procedure these subjects fell behind the others considerably and their data will not be reported.

Prior to being exposed to experimental conditions, the remaining subjects were exposed to five reversals such that they experienced (S)B_1 and (L)B_1 twice. Each reversal lasted at least 15 sessions, but where changed before behavior completely stabilized.

Unequal reinforcer probabilities. The primary conditions of the experiment consisted of exposing subjects to a series of discrimination reversals ((S)B_1 & (L)B_1) in which reinforcer probabilities are equal in some conditions ($p(R_L) = 0.5$) or favor the left or right response alternative ($p(R_L)) = 0.8$ or $p(R_L)) = 0.2$) in other conditions. Each condition lasted 15 sessions. The sequence of experimental conditions, sample-to-comparison mapping, and reinforcer probabilities for each subject are displayed in Table 4.1. Note that conditions in which correct responses were reinforced with equal probability intervened between each condition of unequal reinforcer probabilities. These equal reinforcer probability conditions served as an effective baseline in attempt to reestablish unbiased discriminative performance. According to this design, unequal reinforcer probability conditions occur with the sample stimulus-class, correct-response location mapping for each subject, but differ between subjects (see in Table 4.1). Note that for J108 the same unequal reinforcer probabilities were ran due to an experimenter error.

RESULTS

Repeated Acquisition Performance: Equal reinforcer probability conditions

Each subject experienced ten total discrimination reversals; therefore the two response alternatives were correct following short and long stimulus durations on five separate exposures. Figure 4.3 shows percent correct plotted as a function of session, averaged across the last three exposures to a particular type of reversal. The figure shows that discrimination accuracy increased across sessions for each subject and that whether B_1 responses were correct following either short or long stimulus durations had little effect on the rate of relearning the discrimination or the asymptotic levels of accuracy achieved (supporting Hypothesis 1). Furthermore, each subject exhibited strong carryover effects which manifest as a percent correct for a particular session that falls below 0.5. For subject J107 there was some difference in learning rate across the first three sessions of a reversal when B_1 was correct following short stimulus durations (especially for sessions 2-3) however, this difference disappeared by session five and asymptotic accuracies were similar. For subject J109 there appears to be a difference in the abruptness with which performance reached asymptote. That is, discrimination was similar across the first three sessions for (S)B_1 and (L)B_1, but during (L)B_1 correct responding abruptly reached asymptotic levels at session five.

Although percent correct provides an overall measure of discrimination performance, this measure does not give an indication of the acquisition of stimulus control following any particular sample stimulus duration. Figures 4.4-6 show psychometric functions obtained for each subject, which plot the relative frequency of responses to the correct response location following long stimulus durations as a function of stimulus duration. The data in Figures 4.4-6 come from the same preliminary training sessions as used to construct the percent correct functions portrayed in Figure 4.3. The psychometric functions in Figures 4.4-6 have been grouped by successive blocks of three sessions and have been plotted separately for (S)B_1 (top) and (L)B_2 (bottom).

Although Figures 4.4-6 give the impression that the psychometric functions were flat at the beginning of a reversal, in fact during the first session (and sometimes subsequent sessions, see Fig. 4.3) each rats' performance exhibited strong carryover effects. The upper plot [(S)B_1] for J107 in Figure 4.4 provides evidence of this effect, where responding following a stimulus is in accordance with the previous relation between stimulus duration and correct response location. Therefore, following a reversal, subjects demonstrated a hysteresis effect followed by a fairly smooth rate of learning. Overall, across training sessions the major effect on the psychometric functions is an increase in the range of the function. Comparison of each subjects' psychometric function along with the overall percent correct data presented in Figure 4.3 demonstrate that even at the shortest and longest durations, discrimination was not errorless. The data from the training conditions, in which correct responses were reinforced with equal probability, is therefore consistent with the acquisition data reported by Heinemann and colleagues (Heinemann, Avin, Sullivan, & Chase, 1969; Heinemann & Avin, 1973).

Unequal Reinforcer Probabilities

The major goal of the present study was to track changes in accuracy and response bias (defined as preference for the response alternative with the higher probability of reinforcement) and compare the onset of these performance measures during the course of repeated acquisition. Therefore, beginning with the first session of a reversal, a cumulative percent correct and percent bias measure was calculated for each subject. These curves should converge on the condition-wide percent correct and percent bias as more and more data are included in the calculation. Figures 4.7-4.9 present the cumulative accuracy [Cumulative Correct/(Cumulative Correct + Cumulative Error)] and bias [Cumulative B_{Rich}/(Cumulative B_{Rich} + Cumulative B_{Lean})] measures for each subject separately for each condition in which reinforcer probabilities for correct responses were unequal (see Table 4.1). Each percent bias plot has been constructed so that percent biased responding is for the alternative with the higher reinforcer probability (i.e., location is ignored). Also, the percent bias measure was normalized so that a bias of zero represents equal responding to each alternative.

Figures 4.7-4.9 demonstrate that both discrimination and bias changed in orderly ways as function of training and that these measures were quite consistent within subjects. Discrimination accuracy increased at a high rate within the first three experimental sessions (*Mdn* = 231 reinforcers) and approached asymptotic values after approximately the fifth session. Bias also changed rapidly within the first few sessions of a reversal. Visual inspection of the cumulative bias plots suggests that this aspect of performance approached asymptotic levels faster than discrimination accuracy.

To provide a quantitative summary and comparison of the discrimination and bias measures for each subject a Weibull function was fit to each subjects' data (see Gallistel, Fairhurst, & Balsam, 2004). Applied to the cumulative percent correct and bias data, the function is written:

$$y = A(1 - e^{[(R/L)^S]}) \tag{4.2}$$

where y equals the cumulative performance measure under consideration, *R* is the cumulative number of reinforcers, and *e* is the base of natural logarithms. The parameters *A*, *L*, and *S* are the asymptote, latency, and shape of the function. The asymptote and latency parameters are straightforward, as they represent the asymptotic performance level achieved and the number of reinforcers to half the asymptotic value, respectively. The shape parameter is a measure of the abruptness of onset normalized to latency and allows the Weibull to assume very different functional forms. Small values of the shape parameter ($S < 1.0$) produce a function that is monotonically increasing and resembles other functions used to model acquisition data such as the exponential and hyperbolic. As the shape parameter increases above 1.5, it becomes sigmoidal in shape; asymmetrically so for values less than 2.0 and symmetrically for values of 4.0 and higher.

The best fitting Weibull functions for each subject and condition to the cumulative accuracy and bias measures are also presented in Figures 4.7-4.9. The Weibull functions were fit to each subjects' data via nonlinear least squares regression. Table 4.2 provides parameter estimates and measures of goodness of fit. In general the Weibull function provided an adequate fit to the cumulative performance measures with the exception of the data from J108 in two conditions (conditions 2 & 4). Across subjects and conditions, the onset latency or number of reinforcers to half asymptotic performance was smaller for cumulative bias in seven of nine comparisons, the exceptions being J108 in the second and fourth conditions (partially supporting Hypothesis 2). The shape parameter was greater for the cumulative bias measure in all cases. A closer analysis of the data for J108 revealed that this subject often showed bidirectional changes in bias. That is, this subject often showed a bias towards the higher reinforcer frequency alternative in the first post-reversal session, which dissipated only to appear again a few sessions later. Overall, the analysis of the cumulative discrimination and bias data via fits of the Weibull function demonstrates that the onset of bias appeared before discrimination in the majority of cases and that the onset of bias appeared more abruptly.

Theoretical Analyses of Attending

The primary theoretical motivation of the current study has two parts: 1) to provide a novel test of the attending-augmented DNA model (Nevin, Davison, & Shahan, 2005) by fitting the model to acquisition data and 2) to examine the degree of independence in the models' attending parameters. As stated in the introduction, research using the concurrent-chains procedure to study the acquisition of choice has shown that control over behavior by primary reinforcement and over choice by conditioned reinforcement can be dissociated (Grace, 2002). Specifically, this research has shown that preference which is assumed to be mediated by conditioned reinforcing value develops slower than that maintained by primary reinforcement. The analog of this finding in the present procedure would presumably correspond to observing biased responding to the comparison stimuli before discriminative control by the sample stimuli. The present data are largely consistent with a dissociation among bias and discrimination in signal detection performance. Therefore, the attending version of the DNA model was fit to the obtained data in order to assess the independence of its attending parameters.

The present procedure employed a 6-stimulus, 2-response detection procedure and fitting the DNA model (Fig.4.1) requires 5 parameters measuring the discriminabilities between each pair of sample stimuli ($d_{12}, d_{23}, d_{34}, d_{45}, d_{56}$), a single parameter measuring the discriminability between the two comparison responses (d_r), and an inherent bias term (c) measuring any preference towards a particular response alternative that is independent of the biasing effects of the relative frequency of reinforcement for correct responses. Furthermore, to fit the model to the data from each session of the present experiment requires estimates of the probability of attending to the sample $p(\mathrm{A}_s)$ and comparison stimuli $p(\mathrm{A}_c)$, respectively as a function of training.

In their original proposal of the attending-augmented DNA model, Nevin, Davison, and Shahan (2005) proposed equations from behavioral momentum theory (Nevin & Grace, 2000) to describe the changes in attending to the sample and comparison stimuli as a function of the rate of reinforcement correlated with these stimuli. Preliminary analyses with these equations suggested that the obtained rate of reinforcement did not vary substantially over the course of a condition. That is, although accuracy decreased in the first few sessions of a condition and then rose to high levels thereafter, the rate of reinforcement did not differ enough to produce the large changes in attending probabilities needed to fit the present data. Therefore, rather than using the momentum equations to produce changes in attending parameters, two other candidate functions were employed and compared in their ability to fit the data.

The first equation is the Weibull presented above as Equation 4.2 and its parameters may be interpreted similarly. The second candidate function used to model changes in attending was a simple linear-operator model which has been exploited many times in the study of learning (e.g., Bush & Mosteller, 1955; Rescorla & Wagner, 1972). The Weibull equation again contains three free parameters and these parameters were adjusted such that the probability of attending increased as a function of sessions. The linear-operator equation employed is

$$\Delta A_{x(n+1)} = \alpha(A_{asymp} - A_n) \tag{4.3}$$

where $\Delta A_{x(n+1)}$ is the change in attending probability resulting from a single session of training. The term A_{asymp} represents the asymptotic probability of attending, which was set to 1.0 in the fits, and A_n representing the attending probability in the previous session. The parameter α determines the rate of increase in attending probability.

Note that two separate equations are needed to model increases in the probability of attending to the sample stimuli and comparison stimuli, respectively. Therefore, the Weibull fits require 6 more parameters to be estimated, while the linear-operator requires 2 extra parameters be estimated. The data used for the model fits were the proportion of responses to the alternative deemed correct following a long duration stimulus and were taken from each session from all conditions, providing 270 data points per subject for the fits.

The fits of the DNA model using a Weibull and linear-operator function to describe the increase in attending was carried out by nonlinear least squares regression using the Solver tool in Microsoft© Excel. The parameter estimates and goodness of fit measures for the fits are presented in Table 4.3. The table shows that generally the fits were satisfactory, with small estimates of root mean squared error (RMSE). Furthermore, little difference in the quality of fits was obtained when either the Weibull or linear-operator equations were used to estimate the attending probabilities. Because these models differed in the number of free-parameters *k* employed, the Akaike (AIC) and Bayesian (BIC) information criteria were used to assess quantitatively the tradeoff in goodness of fit and difference in free parameters between the models (Burnham & Anderson, 2002; Pitt & Myung, 2003). The major difference between these criteria is that the BIC penalizes a model more strictly for more free parameters. For both indices, a smaller (more negative) value indicates the model to be preferred. Although the differences between AIC and BIC values were small, each gave a smaller value for the attending model employing the Weibull function. Therefore, further results presented will focus on this model.

Figure 4.10 provides the estimated changes in attending to the sample and comparison stimuli through the course of training plotted as a function of sessions since transition as estimated by the Weibull function. Across subjects, the attending parameters varied considerably. According to the attending model parameters, the probability of attending to the comparison stimuli increased at high rate for subjects J107 and J108, however the opposite effect occurred for subject J109. For all subjects, the probability of attending to the sample stimuli increased either gradually (J107 and J108) or abruptly (J109) with training (partially supporting Hypothesis 3). Attending to the sample stimuli corresponds to States 1 and 2 of Figure 4.2, however only in State 1 can the sample stimuli exert discriminative control over responding. Because the probability of entering State 1 is given by the product of $p(A_s)$ and $p(A_c)$ these values must both increase in order for discrimination performance to improve with training. To the extent that $p(A_c)$ is greater than $p(A_s)$,behavior is governed by State 3 of Figure 4.2 in which behavior is solely controlled by differential reinforcement to the extent that the response alternatives are discriminable from one another. For subject J107, the change in attending probabilities given by the model accounts for the early onset of bias before accurate discriminative control reappears (supporting Hypothesis 3). For subject J108, the probability of attending to the comparisons rises quickly, but then is overtaken by attending to the samples (disconfirming Hypothesis 3). Therefore, the model describes the brief appearance of bias in the first few sessions of a reversal, as well as the slightly poorer discrimination for this subject. The probability of attending to the samples appears maximally within the first reversal session for subject J109 (disconfirming Hypothesis 3). The probability of attending to the comparisons then increases monotonically across sessions. These parameter values imply that for J109, States 1 and 2 governed this subject's performance, which gives a mixture of random responding to the comparisons, and behavior controlled jointly by both sample and comparison stimuli, respectively. The fact that bias appeared before discrimination accuracy for J109, much like that of subject J107, yet the attending parameters differed greatly between these subjects might be accounted for by the much greater values of contingency discriminability d_r obtained for J109 (Table 4.3) which means that reinforcer differences had a greater impact on this subject's performance.

DISCUSSION

The present experiment employed a successive – or repeated-acquisition procedure in which the relationship between classes of short and long sample stimuli and their respective correct comparison location were changed every few sessions. After subjects had experienced several reversals, the probabilities of reinforcement for correct responses following each stimulus class were manipulated. The simultaneous discrimination reversal and reinforcer probability manipulations provided the opportunity to observe the acquisition of both discrimination and bias within individual subjects. The purpose of the experiment was to track changes in both discrimination and bias over the course of acquisition in order to compare the rate of acquisition among these two measures. The secondary goal of the present study was to provide a novel test of a behavioral model of signal detection performance that includes separate theoretical terms representing the probabilities of attending to sample and comparison stimuli, respectively (Nevin, Davison, & Shahan, 2005). Specifically the theoretical goal of the present study was to apply a steady-state performance model to acquisition data. Therefore, it was asked if discrimination and bias can be dissociated during the course of acquisition, then could the model provide independent changes in parameters representing attending to sample and comparison stimuli.

The results from training conditions in which the probabilities of reinforcement for correct responses were equal provided a systematic replication previous of a report by Heinemann and Avin (1973). The present study however, provided within subject replications using a repeated reversal design. The psychometric functions presented in Figures 4.4-4.6 are consistent with Heinemann and Avin's finding that the primary effect of continued training is on the range of the psychometric functions. Heinemann and Avin (1973) also showed that both the midpoint (PSE) and slope of psychometric functions changed throughout the course of acquisition. Although the same quantitative analyses were not performed in this study, the present data are consistent with Heinemann and Avin's contention that the principal effects of continued training are to increase attention to the relevant stimulus dimension.

Over the primary conditions of the experiment, the relation between stimulus class and correct response location were reversed every fifteen sessions. Every other condition also introduced a biasing manipulation in which the relative frequency of reinforcement for correct responses was unequal. These two manipulations allowed for the simultaneous assessment of the acquisition of discrimination and bias. The key dependent variables were the cumulative percent of responses correct and the cumulative percent of responses to the alternative with the higher probability of reinforcement. To provide a quantitative assessment of acquisition, a Weibull function including estimates of asymptotic performance, latency to half-asymptote, and the abruptness of the onset were fit to each subjects' acquisition curves. The Weibull analyses (Table 4.2) showed that the onset of bias occurred before discrimination as measured by latency in seven of nine cases and that the onset of bias was more abrupt on all nine occasions. These data are the first, to my knowledge, to demonstrate a dissociation between discrimination and bias during acquisition in a signal detection procedure.

Nevin, Davison, and Shahan (2005) provided an extension of an earlier model of signal detection performance (see Davison & Nevin, 1999) which includes a role for attending based on the rate of reinforcement correlated with sample and comparison stimuli. This model was fit to the acquisition data of the present experiment. Fitting the model to the present data required modification of the originally proposed equations that modulate the probabilities of attending. Nevin et al. suggested that attending in conditional discrimination procedures increased with the rate of reinforcement correlated with sample and comparison stimuli according to equations derived from behavioral momentum theory (Nevin, 1992; Nevin, Mandell, & Atak, 1983; Nevin & Grace, 2000). The discrimination reversals produced only small changes in the obtained rate of reinforcement in the present experiment. Therefore, two other candidate functions were used to model the changes in attending probabilities as training within a condition progressed. A comparison of both candidate functions showed that the increase in attending probabilities by a three-parameter Weibull function provided a better account of the present data than did a one parameter linear-operator equation.

The overall performance of the attending-augmented version of the DNA model were good considering the model was developed for steady-state application and the present data are the first attempt to apply the model to acquisition data. The parameters measuring the discriminability among sample stimuli and comparison stimuli were largely consistent with results from Experiments 1-2. The major discrepancy between the data and model predictions arose from the first few sessions after a transition (not shown). This is because the DNA model with attending probabilities set at zero produce flat psychometric functions; whereas the data from the first post-reversal sessions resembled an inverse S-shaped functions. The model might be adapted to account for these carryover effects, but this would require the addition of further parameters. It is not exactly clear how best to incorporate carryover in the present procedure, so no attempt will be made here.

It should be noted that while the attending version of the DNA model applied to the present experiment contains several free parameters (13 were required in the Weibull function fits), other models would require a similar number if not many more parameters. An attempt to model the present data using, for example, a four-parameter cumulative normal function would require several times the number of parameters used here. Although not reported, the analysis reported by Heinemann and Avin (1973) using a cumulative normal function with lower and upper asymptotes, likely employed forty free-parameters per subject. Perhaps a simplification of Heinemann and Avin's analysis could be achieved by holding some parameters constant, but it is unclear which should be held constant and such an attempt was not made here. Furthermore, the DNA model provided an account of the present data with parameters representing the discriminability among sample stimuli and comparison stimuli, respectively that remained fixed across conditions and training sessions and is therefore a more parsimonious treatment.

Finally, the constancy of stimulus and contingency discriminability parameters across the course of acquisition has several implications for discrimination learning. The attending-augmented DNA model implies that the discriminability among sample stimuli and comparison stimuli do not change across reversals. According to the model, discriminability terms are psychometric distances which are long-term structural features of the environment and the sensory capacities of the specific species and individual organism under study. What changes across training, according to this model, is the probability with which subjects attend or engage in observing behavior directed towards the sample and comparison stimuli. In turn the probability of observing the relevant stimuli is a function of their correlation with primary reinforcement, the conditioned reinforcing value of these stimuli. In the present study, reinforcer rates were not directly manipulated, however the correlation between a class of sample stimuli and the correct comparison location were reversed every few sessions. Thus, the correlation between a particular sample stimulus and its correct comparison was disrupted. The attempt to model the changes in attending probabilities as a function of training directly parallels that of associative learning models that describe the acquisition of a conditioned response (e.g., Rescorla & Wagner, 1972; for recent reviews see Pearce & Bouton, 2001; Wasserman & Miller, 1997). Therefore, the present analyses suggest that the learning process in signal detection may be primarily due to contingency variables and future research on discrimination learning should be directed towards an analysis of these processes.

CHAPTER 5

GENERAL DISCUSSION

The research reported in this dissertation was conducted with two general aims: 1) to develop a dynamic research methodology that allows for a characterization of learning in signal detection procedures, and 2) to apply static models of detection performance to performance in transition and therefore provide a test of some of the assumptions of these models. Such a research methodology would allow for the dynamic characterization of the key performance measures in a signal detection procedure: discrimination and bias. In turn, a dynamic characterization of discrimination and bias would presumably shed light on whether these measures are truly independent as well as the basic learning mechanisms that produce these asymptotic performance measures. Chapters 2 and 3 reported experiments examining the extent of within-session changes in response bias in both simple and complex signal detection tasks when the consequences for correct responses changed randomly from session to session. Chapter 4 reported an attempt to study learning of discrimination and response bias simultaneously by employing a successive reversal design in which the correct response location following a stimulus class was changed every few sessions.

The experiment reported in Chapter 1 was the first attempt to apply a method of frequently varying the relative frequency of reinforcement among concurrently available response alternatives to a signal detection task. Specifically, Experiment 1 employed a pseudorandom binary sequence where the probability of reinforcement for correct responses can change between two reciprocal values (3:1 and 1:3) each session. Across two conditions, the difference between sample stimulus durations was manipulated such that in one condition the discrimination was more difficult than in the other. The DNA model of detection (Alsop & Davison, 1991; Davison & Nevin, 1999) was extended to incorporate the possible effects of previous sessions' reinforcer frequency ratios and thus quantify any carryover effects of response bias. The two major findings of Experiment 1 were that at the session-aggregate level, response bias was largely unaffected by previous sessions' reinforcer ratios (Fig. 2.4) and that the degree of adaptation to the current session reinforcer ratio differed across conditions (i.e., discrimination difficulty). In the condition were discrimination was most accurate, response bias increased monotonically within experimental sessions (Fig. 2.5), which according to the model, was due a decrease in the effect of the previous session's reinforcer ratio and an increase in control by the current session reinforcer rate ratio. In the condition were discrimination performance was less accurate, session-aggregate response bias was also reduced. Within-session analyses revealed little difference between the effects of previous and current session reinforcer ratio (Fig. 2.6). The condition 2 data of Experiment 1 provide no indication as to whether something about the within-session dynamics themselves or the difference among sample stimuli contributed to the reduced response bias observed in the second condition. It is unlikely that the within-session dynamics are the reason for the difference as the data from the first condition of Experiment 1 and data from Experiment 2 suggest an orderly within-session adjustment to current session reinforcer ratios. It is possible that if subjects mediated the to-be-timed stimuli by their own behavior, then contingency discriminability decreased as a result of similarity of classes of mediating behavior. While this suggestion is plausible, as behavioral mediation of temporal intervals is well established in the literature (Laties, Weiss, & Weiss, 1969; Killeen & Fetterman, 1988; Richelle & Lejeune, 1980; Staddon & Simmelhag, 1971), no systematic observations of behavior during sample presentations were made in Experiment 1.

Experiment 2, reported in Chapter 3, provided a systematic replication of Experiment 1. Rather than presenting different stimuli across experimental conditions, however Experiment 2 employed an *n*-stimulus procedure in which five different sample stimuli were presented in each session. Again, like Experiment 1, the probability of reinforcement for correct responses varied from session-to-session according to a pseudorandom sequence, however in some sessions of Experiment 2 the reinforcer probabilities were equal. The extension of the pseudorandom sequence design to an *n*-stimulus procedure is important because it allows for simultaneous assessment of response bias at a range of discrimination accuracies. Furthermore, Experiment 2 provided a test of an *n*-stimulus model of detection proposed by Davison (Davison, 1991; Davison & Nevin, 1999) which asserts that each reinforcer delivery contingent on a particular correct response in such procedures affect all other stimulus-response pairs to the extent that each are similar to one another. The major results of Experiment 2 replicated the findings of Experiment 1 in that, after sufficient exposure to the pseudorandom sequence, aggregate performance in a given experimental session was predominately under control of the current session's reinforcer ratio (Fig. 3.3). Analyses of within-session performance showed an approximately monotonic decrease in control by the previous session's reinforcer ratio along with an increase in control by the current session reinforcer ratio (Fig. 3.4). Further analyses, at a trial-by-trial level, showed that response bias appeared very early in a session, often within a few presentations of a given sample stimulus (Figs. 3.6-8). The ability of an extended form of Davison's *n*-stimulus detection model to capture both session-aggregate and within-session changes in control by previous and current reinforcer ratios, in addition to the rapid changes in bias following each sample stimulus, suggest that assumptions of the model may be profitably extended to dynamic performance.

Finally, in Chapter 4, an experiment was reported in which the development of both discrimination and bias were examined simultaneously. Experiment 3 employed a 6-stimulus classification task in which one response was correct following the three shorter stimulus durations and another response was correct following the three longer durations. The correct response location following each stimulus class was switched across successive blocks of sessions. In the major conditions of the experiment, the reversal between stimulus class and correct response location continued, however every other reversal included unequal reinforcer probabilities for correct responding following the two stimulus classes. Therefore, these experimental conditions allowed for a simultaneous assessment of the speed of acquisition of discrimination and bias simultaneously. Although asymptotic levels of discrimination and bias differed, the time to half-asymptotic levels was shorter for bias on seven of nine occasions. Analyses of the development of performance by an attending-augmented version of the Davison-Nevin-Alsop model of detection were performed. This model includes separate roles for the sample and comparison stimuli in determination of detection performance. The test of this model involved assessing whether the attending parameters of the model took on consistent values across subjects in order to predict the faster onset of bias that was observed. Although the model gave an accurate quantitative description of the development of discrimination and response bias, the model's attending parameters differed widely across subjects. Therefore, the data from Experiment 3 showed a clear dissociation of discrimination and bias during acquisition, however theoretical analyses based on the attending-augmented DNA model did not reveal a common mechanism that might be hypothesized to bring about the observed performance dynamics.

There were a few notable differences between the findings of Experiments 1 and 2. Both session aggregate estimates of lag 0 d_r and within-session control by the current session reinforcer ratio were highest in the easier discrimination condition of Experiment 1 and lowest in the more difficult discrimination condition. The estimates of control by current session reinforcer ratios were intermediate in Experiment 2 relative to that observed in the two conditions of Experiment 1; also a small effect of the previous sessions' reinforcer ratio was evident throughout most of the session. It remains puzzling that in Experiment 1, contingency discriminability was lower when the S_1-S_2 difference was small, however, in Experiment 2 the same stimuli were all presented within session yet a constant value of d_r provided an adequate description of the effects of the reinforcer frequency ratio. Godfrey and Davison (1999) showed that the DNA model provided consistent estimates of both d_s and d_r when different sample and comparison stimuli were added and removed from a set of up to five sample and comparison stimuli. Of course, comparing estimates of contingency discriminability across Experiments 1 and 2 of the present study is difficult as different subjects were used in each and exposure to the PRBS was much shorter in Experiment 1.

Perhaps the most consistent finding across each experiment reported was the speed of changes in bias. In Experiments 1 and 2, where reinforcer ratios changed each session, rapid changes in bias were expected (Schofield & Davison, 1997). The observed changes in bias in Experiment 3 were however, at least as fast when taking into account the speed of environmental change in that experiment. A review of recent studies investigating choice behavior in transition suggests that the speed of behavior change is partly dependent on the frequency of environmental change. These studies have varied the reinforcer ratio either within each session (Davison & Baum, 2000), between sessions (Hunter & Davison, 1985), or across several sessions (Mazur, 1997) and the speed of behavioral adaptation is faster when change is more frequent. Therefore, it would seem likely that response bias should have been much slower to develop in Experiment 3. This was not the case. Across subjects, the number of reinforcers to 50% of eventual asymptotic response bias was 120 reinforcers, which corresponds to the second post-reversal session. Thus, even when reinforcer contingencies changed at a much slower rate in Experiment 3, bias still adapted very quickly. While the broader implications of the speed of changes in bias will require further research, these findings may prove to be consistent with a single-process learning view where sensory processes are secondary to a locally driven, reinforcement-dependent behavioral mechanism.

Finally, the most notable differences among the present experiments is that stimulus variables were held constant in Experiments 1 and 2, while the discriminative function of the stimulus classes and biasing variables were both manipulated in Experiment 3. Therefore, Experiments 1 and 2 only investigated acquisition of bias with stimulus conditions held constant and Experiment 3 investigated acquisition of discrimination and bias. Future research may employ designs like that of Experiments 1 and 2 in order to compare acquisition of bias under manipulations other than reinforcer frequency. Designs like that of Experiment 3, however are indispensable when investigating the concurrent development of discrimination and bias, and thus the independence of learning mechanisms responsible for both performance measures.

Assessment of Dynamic Methodology

Overall, the methodology employed in the experiments reported here was successful in that the transition data were orderly and aggregate data replicated previous findings. Therefore, the methods employed here may prove to be viable alternatives to traditional steady-state experimental designs employed in the experimental analysis of behavior (Sidman, 1960). The use of more dynamic experimental designs allow for the manipulation of several independent variables in a substantially shorter time frame. Furthermore, such designs are excellent for rats, which are short-lived, or people, who have limited time to participate in experiments. Rats also provide a mammalian model, which may be useful for investigating the biological bases of learning. Moreover, the use of dynamic designs which produce rapid adjustment to experimental contingencies provide numerous possibilities for the investigation of behavior in transition.

The ability to conduct large parametric studies within a reasonable time frame is of increasing importance. Researchers in the area of signal detection, like those investigating simple choice in other paradigms, are typically interested in understanding the effects of several variables on performance simultaneously (i.e., Elliffe, Landon, & Davison 2008). Therefore, it may be reasonable to ask how many variables may be manipulated in a random fashion across experimental sessions (i.e., pseudorandom sequence designs) while being able to maintain experimental control. A recent study reported by Kyonka and Grace (2008) manipulated two (Experiment 1) and three (Experiment 2) dimensions of reinforcement according to independent pseudorandom sequences in the context of a concurrent-chains procedure. They found that control by each reinforcer dimension developed within each session and that both session aggregate and local measure of performance supported the assertion of molar models that each reinforcer dimension has an independent effect on behavior.

The report of independent effects by different dimensions of reinforcement by Kyonka and Grace (2008) is an important one as quantitative analyses become more pervasive (Mazur, 2006). Schofield and Davison (1997) argued that the PRBS methodology may be a profitable way of measuring sensitivity to reinforcement. Thus designs like the PRBS are critically important for future advances where model parameters become fundamental dependent measures. Therefore, it seems that rapid estimation of higher-order dependent measures is of special importance in the area of signal detection research. Experiment 3 suggests that the usual model parameters that have been estimated in detection experiments may not even be the most critical determinants of performance. That is to say, measures such as stimulus and contingency discriminability may be best conceptualized as long-term structural features of the task and subject. Whereas performance variables, such as the conditioned reinforcing value of the sample and comparison stimuli, may ultimately determine the level of discrimination or bias observed with stimulus differences held constant.

Implications for Theory

The central theoretical goal of the present experiments was to extend current theory to detection performance in transition. This was done by extending previous quantitative models of signal detection performance to the present studies in which both stimulus and reinforcer variables were manipulated over much shorter time scales than that of experiments typically reported in the literature. In other words, most prominent models of detection performance have been formulated to describe stable performance; however the present research sought to extend these models to detection performance in transition. As discussed in Chapter 1, a model proposed by Davison, Nevin, and Alsop (Alsop & Davison, 1991; Davison & Nevin, 1999) is currently the most prominent model of detection and conditional discrimination performance in the non-human literature. Although some failures of this model have been noted (Jones, 2003), and modifications have been proposed (Nevin, Davison, & Shahan, 2005), the model is more broadly applicable and its assumptions are more easily testable than its generalized matching-based predecessor(s) (Davison, 1991; Davison & Jenkins, 1985; Davison & Jones, 1998; Jones & Davison, 1998). The success of extending this theory was evaluated both in the ability of the model to fit transition data and by the extent to which the assumptions of the model were upheld. Furthermore, applying the most widely utilized model in the literature to detection performance in transition should prove advantageous in pointing out gaps in current understanding.

Beginning with Experiment 1, reported in Chapter 2, the DNA model of detection performance was extended to incorporate the effects of previous sessions' reinforcer ratios on current session performance. This was done by assuming that the effect of current and previous sessions' effective reinforcer ratios combined additively to produce current session levels of bias. Because within an experimental condition the difference among sample stimuli were held constant, the parameter measuring stimulus discriminability d_s were held constant across sessions. The influence of current and previous effective reinforcer ratios on response bias in the current session was modeled by allowing for individual contingency discriminability parameters (d_r) in determining each session's effective reinforcer ratio. With stimulus discriminability held constant, an increase in contingency discriminability results in a negatively accelerated increase in response bias for the higher reinforcer frequency alternative.

The extension of the DNA model to both session aggregate (Fig. 2.4) and within session (Fig. 2.5-6) changes in bias provided an accurate description of the data from both conditions of Experiment 1. Furthermore, the degree of control by current and previous sessions' reinforcer ratios was similar to that reported in research were the PRBS method has been used to study preference in concurrent and concurrent-chained schedules and similar analyses were performed (Davison & McCarthy, 1988; Grace, Bragason, & McLean, 2003; Kyonka & Grace, 2008; Schofield & Davison, 1997).

Perhaps the most notable result of Experiment 1 was that estimates of contingency discriminability decreased across conditions when the difference among sample stimuli was manipulated. Thus, as the sample stimuli were made more similar, the parameter measuring the difference among comparison stimulus locations changed. A reanalysis of an experiment reported by McCarthy and Davison (1980) suggests that the observed parameter covariation was not due to the use of the pseudorandom sequence procedure. While other studies have reported parameter covariation (Nevin, Cate, & Alsop, 1993), it may be possible that this finding is due to the use of temporal stimuli (Ward, 2008). The DNA model has only been applied to a few detection studies employing temporal stimuli, but to my knowledge each has found some parameter covariation. Therefore, further analyses of temporal discrimination performance by the DNA model are warranted before a definitive conclusion can be offered. This is not to suggest that temporal stimuli are necessarily unique, the majority of research suggests that the psychophysics of time are similar to other stimulus dimensions (Gibbon, 1977; Killeen & Weiss, 1987). It may be, however that the unequal delays to reinforcement that are inherent in temporal discrimination procedures pose difficulties for the contemporary models as it is uncertain how to relate the value and discriminability of reinforcers (Alsop & Porritt, 2006; Davison & Nevin, 1999; Nevin, Davison, Odum, & Shahan, 2007).

The experiment reported in Chapter 3 provided another opportunity to evaluate an extension of the DNA model to account for possible carry-over effects. The extension of the model to Experiment 2 provided a more challenging assessment because the study employed an *n*-stimulus procedure. Application of the DNA model to an *n*-stimulus procedure allows for a more thorough evaluation of the way in which the model conceptualizes the spread of effect of reinforcement between sample stimuli and comparison responses. The DNA model was applied to the data of Experiment 2 as above with the following modification: four d_s parameters were used to estimate discriminabilities between each pair of stimuli. As in Experiment 1, separate contingency discriminability parameters were used to assess the effects of past and present effective reinforcer ratios, and the stimulus discriminability parameters used to estimate effective reinforcer ratios were constrained to be constant. Again the extension of the DNA model including past effective reinforcer ratios provided an accurate account of the data. Both session-aggregate and within-session changes in bias were well accounted for. Additionally, the predicted changes in control by the current and previous sessions' reinforcer ratios provided an excellent description of the psychometric functions obtained from the latter portion of experimental sessions.

Although the analyses conducted in Experiments 1 and 2 and discussed above provided a reasonable way of characterizing the rapid changes in bias observed in those studies. It is important here to note that modeling the observed changes in bias with different estimates of contingency discriminability is incoherent given the particular theoretical interpretation offered here. Recall that contingency discriminability (d_r) is assumed to be a measure of the psychological distance between comparison responses. In the present experiments d_r is assumed to be a function of the difference in the spatial locations of the levers. Therefore, as d_r is defined, suggesting that the discriminative impact of the distance between levers changed within an experimental session or as a function of changes in the reinforcer ratio makes little theoretical sense.

It is important to note that d_r has been interpreted differently throughout the development of the DNA model (Davison & Nevin, 1999; Nevin, Davison, Odum, & Shahan, 2007; Nevin, Davison, & Shahan, 2005). The interpretation of d_r assumed in the present work is based on the model's forbearers from the psychophysics literature (Luce, 1959; Shepard, 1958a, 1958b) as different interpretations have been given (Davison & Nevin, 1999). In their original presentations of the model, Alsop (1991) and Davison (1991) suggested that d_r was a measure of the discriminability among response alternatives in standard detection (i.e., "yes-no") procedures, which is consistent with Shepard's (1957) and Luce's (1959) interpretations. When Davison and Nevin (1999) extended the model to conditional discrimination procedures where response location and comparison stimuli varied across trials, they suggested that d_r could also provide a measure of discriminability among comparison responses. They assumed that response location and comparison stimulus disparity produce functionally equivalent effects on behavior and, thus, that a single parameter (d_r) was sufficient. Jones (2003, personal communication, May 22, 2009) has argued that the contingencies in matching-to-sample procedures are more complex than simple detection and involve multidimensional comparison stimuli (see Alsop & Jones, 2008). It may be that previous modeling efforts have all allowed the effects of several different independent variables all of which may contribute to contingency discriminability to be absorbed by a single free parameter, d_r (c.f., Davison & Baum, 2007; Jones & Davison, 1998; Nevin, Cate, & Alsop, 1993). Although these theoretical objections were anticipated, the modeling reported seemed to be the most reasonable means of communicating the effect of the experimental manipulations. In addition, it may be argued that the ability of the DNA model to account for changes in bias with changes in contingency discriminability with comparison stimulus differences held constant suggests that the model may be too flexible. I will return to the issue of model flexibility after discussing the attending version of the DNA model.

The data presented in Experiment 3 were modeled by employing the DNA detection model assuming that attending to the sample and comparison stimuli were disrupted following each reversal of the discrimination. As discussed in Chapter 4, the attending-augmented DNA model assumes that the probability of attending to sample and comparison stimuli, respectively is a function of the rate of reinforcement correlated by those stimuli (Nevin, Davison, & Shahan, 2005). Because the rate of reinforcement was only indirectly affected by the discrimination reversal and the range of variation in overall reinforcer rate was too small to produce the changes in attending probabilities required to fit the data, other equations assuming increases in attending probabilities with continued training were used to model the data.

Assuming probabilities of attending to the sample and comparison stimuli increasing as a function of amount of training according to a sigmoidal acquisition function provided an accurate description of the data. Therefore, the analyses reported in Experiment 3 provide mixed support for the attending-augmented DNA model. First, the analyses provide support for an attending model. Because subjects had substantial experience with the procedure, employing various stimulus and contingency parameters to model discrimination acquisition is theoretically incoherent. What seems to change during the learning of a discrimination is the behavioral impact or expression of the psychological distances among the sample and comparison stimuli as learning progresses. Whether a learning-performance distinction in signal detection performance is warranted awaits further research. Second, the present research suggests that the probability of attending to the relevant stimuli in a discrimination task, particularly during learning, is not only affected by stable rates of reinforcement but to changes in the conditional relation between discriminative stimuli and reinforcement. For this reason, formulations of attending based on stable rates of reinforcement may be successfully applied to steady-state performance; however other ways of defining the value of discriminative stimuli (Wixted, 1989) are worth exploring to extend current theory to the learning processes.

Finally, I will comment briefly on the flexibility of the DNA model, in particular with respect to the addition of attending parameters to the model. In their initial presentation of the attending-augmented model, Nevin, Davison, and Shahan (2005) discussed the degree to which changes in the attending parameters and discriminability parameters produced similar effects in predicted discrimination accuracy and response bias. Furthermore, they illustrated via simulated plots that while the probability of attending to the sample $p(A_s)$ and stimulus discriminability d_s

produced distinguishable affects, variation in comparison attending $p(A_c)$ and contingency discriminability d_r parameters did not lead to distinguishable predicted functions. Thus, the similar abilities of the two parameters to produce similar predictions was noted from the outset, however Nevin and colleagues suggested that because attending to the comparisons and contingency discriminability are identified with different experimental operations the effects of each parameter should be empirically distinguishable. The present discussion suggest that at the very least, future research should specifically address the role of comparison stimuli in detection performance and perhaps the most proximal increases in understanding will come from the resolution of this issue.

The Spread of Effect

The present research has several implications for other research domains as well as direct application. To study signal detection performance in the laboratory necessitates an analysis of several fundamental determinants of behavior. Thus, it should not be surprising that basic laboratory research on detection performance can be informative to both researchers and practitioners in a number of areas. Historically, signal detection methods and analytic techniques have been applied to a number of areas in decision making and diagnostics (Swets, 1988, 1992; Swets, Dawes, & Monahan, 2000). While these areas of application remain important and the present research can contribute, here I will instead outline some implications that specifically relate to an improved understanding of detection and discrimination learning.

A historically important area of application of basic behavior analytic principles has been in the domain of developmental disabilities. Laboratory research on stimulus control has had a prominent role in the transfer of technology to applied settings (Skinner, 1953; Stokes & Baer, 1977). More recently, a number of investigators have become increasingly concerned with the basic processes involved in discrimination learning (Dube & McIlvane, 2002; McIlvane & Dube, 2003; McIlvane, Dube, & Callahan, 1999). With the hope that a more thorough understanding of the role of attention in the acquisition of a discrimination may provide caregivers with better tools for more effective instruction for individuals with severe developmental disabilities (McIlvane, Dube, & Callahan, 1999). For example, the concept of stimulus control shaping (Sidman & Stoddard, 1967), which directly parallels response shaping, has been used to train individuals with developmental disabilities to discriminate among different forms (i.e., an upright versus inverted T). Thus, interventions that increase the conditioned value of stimuli should increase attending to them, which in turn ought to facilitate learning about stimulus function.

As with the direct application to teaching methods, another important contribution of the present work may be a more comprehensive understanding of the necessary conditions to establish more effective consequences and more persistent socially-appropriate behavior for individuals with developmental disabilities (Dube & McIlvane, 2002; Dube, McIlvane, Mazzitelli, & McNamara, 2003; Mace, Mauro, Boyajian, & Eckert, 1997). While the generalized matching law has proven to be of substantial applied importance (McDowell, 1981, 1982; Pierce & Epling, 1995), basic laboratory research had begun to question its conceptual value (cf. Davison & Jenkins, 1985; Krägeloh, Elliffe, & Davison, 2006). Therefore, considerations based on the contingency discriminability model would lead practitioners to different conclusions about the insensitivity to concurrent sources of reinforcement in populations with developmental disabilities and therefore lead to other intervention strategies (McIlvane & Dube, 2003). For example, the contingency discriminability model may suggest where the disparity between the intervention and the actual environmental contingencies exist. To the extent that discriminative stimuli are improperly arranged for the individual, the developmental disabled individual's perception of what behavior effectively produces reinforcement may differ from that of the practitioner.

The present research also has numerous applications in several areas of neuroscience. A rapidly growing subfield of neuroscience called neuroeconomics (Glimcher, 2002; 2003; Glimcher & Rustichini, 2004), has employed both similar procedures and analyses as those employed in the present research (Gold & Shadlen, 2007; Sugrue, Corrado, & Newsome, 2004). As suggested by the name, the goal of neuroeconomics is to provide converging principles and experimental techniques toward the goal of understanding choice and decision making at both behavioral and neural levels. A number of researchers have utilized complex choice procedures and single cell recordings of neurons in various areas of nonhuman primate cortex in their work (Sugrue, Corrado, & Newsome, 2005). Moreover, Sugrue and colleagues (2005) have argued that the goals of such research are best served by combining an analysis of the local determinants of individual choices with momentary changes in the underlying neurophysiology. A critical aspect of this research involves correlating the activity of a given set of neurons with the estimation of the local value of an animal's choices by various reinforcement learning algorithms (Barraclough, Conroy, & Lee, 2004; Lau & Glimcher, 2008; Sugrue, Corrado, & Newsome, 2005). Accordingly, future efforts to model learning processes in signal detection can easily be exported to aide researchers seeking to understand the neural mechanisms of perception and decision making.

Other active areas of research in the neurosciences are concerned with the neurobiology of reinforcement (Schultz, 1998, 2002, 2007) and changes in reinforcement due to disorders, lesions, and exposure to environmental contaminants. As in the study of neural mechanisms of choice and valuation discussed above, accurate characterizations of neurobiological mechanisms of reinforcement are frequently enhanced by well-established behavioral theories (Schultz, 2004, 2006; Schultz, Dayan, & Montague, 1997; Schultz & Dickinson, 2000). Formal behavioral theories of reinforcement are often advantageous, particularly when reinforcement processes are disrupted.

For example, in laboratory animal models of attention-deficit/hyperactivity disorder (ADHD), Sagvolden and colleagues (Sagvolden, Johansen, Aase, & Russell, 2005) have suggested that deficits in catecholamine function produce a reinforcement deficit. Sagvolden and colleagues have advanced a behavioral theory proposing that the changes in reinforcement functioning for ADHD diagnosed individuals may be a result of a steepened delay of reinforcement gradient. Their account suggests that the ability of reinforcers to couple with the responses that produce them may be altered in ADHD diagnosed individuals. That is, the delay of reinforcement gradient becomes shallower for these individuals. An alternative account would suggest that altered dopamine function may result in a decreased contingency discriminability value for affected individuals. To bring a contingency discriminability account to bear on such a problem requires extending the model to estimate the discriminability among both concurrently and successively occurring instances of behavior. Johansen and colleagues (Johansen et al, 2009) suggest a number of interventions based on their proposed behavioral mechanism. Many of them consist of employing stimuli to bridge gaps between behavior and reinforcement and presenting stimuli that better capture attention. Basic laboratory research on changes in attending and contingency discriminability processes may suggest other intervention strategies.

Future Directions

Each experiment reported here has made use of methods that are novel to the area of signal detection research. Consequently, these experiments have raised far more questions than they have answered. The use of dynamic experimental procedures in the quantitative analysis of behavior has only really begun (Davison, 1998). As a result, numerous avenues for future research on the dynamics of signal detection performance exist. Here I will briefly sketch what I think may be the most promising future directions.

Several recent findings from Davison, Baum, and colleagues have highlighted the importance of the discriminative properties of reinforcer sequences in governing choice at the local level. In their procedure, (Belke & Heyman, 1994; Davison & Baum, 2000) subjects are exposed to seven different unsignaled relative reinforcer frequency ratios in different components, each of which is separated by a 10 s blackout and lasts until 10 reinforcers are obtained. Davison and Baum (2000) found that the rate of change in relative response rate as a function of the relative reinforcer frequency increased as reinforcers were earned within a component. By the end of a component, the slope of the relation between relative response and reinforcer frequency was slightly less than that obtained in traditional steady-state designs (Baum, 1974, 1979; Wearden & Burgess, 1982). To investigate the choice dynamics within this procedure, Davison and Baum (2000) plotted the obtained preference level between each successive reinforcer obtained within components. That is, preference, scaled as the logarithm (base 10) of the left/right response ratio, was plotted for each possible sequence of reinforcers obtained from responding to the left and right response alternatives, respectively. Davison and Baum reported that the effect of a single reinforcer obtained from one alternative that interrupted ("discontinuation") a sequence of reinforcers obtained from the other alternative had the greatest effect on choice. Thus, a single discontinuation produced large changes in preference towards indifference, whereas continuations or successive reinforcers obtained from the same alternative had diminishing effects upon preference.

Findings such as those discussed above have important implications for models of performance in conditional discrimination and signal detection procedures. Existing models of conditional discrimination performance (Davison & Tustin, 1978; Davison & Nevin, 1999) do not directly address the issue of whether discriminative stimuli and reinforcers exert simultaneous control over behavior on each trial or whether behavior on any given trial is under control of only one these dimensions. The model offered by Davison and Tustin (1978) predicts that the effects of sample stimuli and relative reinforcer frequency have independent effects on performance. This might seem to imply that the model would predict that behavior is under joint control by these two sources on each trial. However, the model is actually silent on the issue, as it was originally formulated for steady-state procedures and furthermore, the independence assumption has not held up in some studies (Alsop & Davison, 1991). The model of Davison and Nevin (1999) predicts that the control exerted on behavior by the discriminative stimuli and relative reinforcer frequencies interact to determine performance. In fact, Davison and Nevin state (pp. 449) that the processes invoked by their model are sequential and dynamic, suggesting that discriminative stimuli and reinforcers interact to determine the effective value of each choice alternative on a trial-by-trial basis. Testing either of these sets of assumptions empirically is made difficult by the nature of conditional discrimination procedures. Signal detection and conditional discrimination procedures involve discrete trials in which only a single response is made at a time. Thus, analyses of behavior at a local level in these procedures are more difficult than in other procedures used to investigate choice (Davison & Baum, 2000). Other measures of performance in signal detection and conditional discrimination procedures may, however, produce orderly changes at a local level.

Alsop and Rowley (1996) reported a series of analyses on the local effects of reinforcers on relative response frequency and choice latency in a simple detection task. They found that choice latencies tended to be faster on trials immediately following reinforcement. Further analyses of response bias on trials immediately following reinforcement showed some evidence of a preference for the response alternative correlated with a higher reinforcer frequency. Analyses at this level provided no systematic changes in discriminability. Therefore, the relation between

Alsop and Rowley's (1996) findings on preference immediately following reinforcement differ from those in concurrent schedules (Davison & Baum, 2000; 2002) and the lack of systematic data reported by the authors on trial sequence effects cannot be directly compared to those reported previously (White, Parkinson, Brown, & Wixted 2004).

It seems that some particularly promising future directions involve designs like those employed in the present experiments and an even greater emphasis on analyses of local performance. The most important goal of this research would be to characterize subjects' choices on a trial-to-trial level as a function of the effects of individual reinforcers and the generalization of these effects due to stimulus and contingency discriminability and local reinforcer value. The aforementioned experimental work may allow for the development of an exclusively local model to explain molar performance in signal detection procedures.

Conclusion

In conclusion, this dissertation has shown that dynamic research methodologies from other domains, adapted to the study of signal detection performance, are valid instruments by which to study aspects of conditional discrimination learning. Moreover, discrimination performance and response bias adapt rapidly to frequent changes in experimental contingencies. Extant quantitative models formulated to describe static signal detection performance can be readily adapted to describe such performances in transition. These models provide accurate quantitative descriptions of the transition data; however some theoretical assumptions are violated. Therefore, an emphasis on detection performance in transition will require modification of current theory. Conventional thinking about which model parameters give rise to stable levels of discrimination accuracy and response bias, suggest that modifications to existing models must include a role for the conditioned reinforcing value of sample and comparison stimuli during the course of learning.

Table 1.1

Outline of the Experiments presented in each Chapter. The number of stimuli presented in an experimental session and the mapping between stimuli and correct responding is indicated. Also indicated is the relative frequencies of reinforcement for correct responses that were studied in each experiment. The number of sessions for a given condition within each experiment is also given. The variables that either changed or were held constant for a condition is discussed in the text.

		Short	Long	Reinforcer	Sessions per
Experiment	Stimuli	Correct Response		Ratio	Condition
1	2*	B_1	B_2	1:3;3:1	31
2	5	B_1	B_2	1:3,1:1,3:1	36
3	6	B_1 or B_2	B_1 or B_2	1:4,1:1,4:1	15

* In Experiment 1, 2 stimulus durations were presented each session, but the durations changed across conditions.

Table 3.1

Parameter estimates from fits of the DNA model to the data shown in Figure 3.5. Estimates of contingency and stimulus contingency discriminability, inherent bias, and percent variance accounted for are shown for each subject. See text for further explanation.

	J93	J94	J99
d_{s12}	1.0	1.0	1.0
d_{s23}	14.8	8.7	5.6
d_{s34}	3.0	4.4	2.6
d_{s45}	29.2	38.5	36.8
c	0.5	0.8	0.7
$d_{r(n)}$	7.8	10.8	7.4
$d_{r(n-1)}$	1.0	1.1	1.4
MSE	0.005	0.001	0.004
$\mathbf{R^2}$	0.941	0.985	0.952
m	1.07	1.01	0.98
b	-0.06	-0.02	-0.02

Table 4.1.

Order of conditions for Experiment 3. Rows indicated the sample-to-comparison stimulus mapping for each condition and the probabilities of reinforcement for correct comparison responses.

	J107		**J108**		**J109**	
Condition	B1	p(R|s)	B1	p(R|s)	B1	p(R|s)
1	Short	0.5	Long	0.5	Short	0.5
2	Long	0.2	Short	0.2	Long	0.2
3	Short	0.5	Long	0.5	Short	0.5
4	Long	0.8	Short	0.2	Long	0.8
5	Short	0.5	Long	0.5	Short	0.5
6	Long	0.2	Short	0.2	Long	0.2

Note – Listed under B_1 is the stimulus class for which responses to right lever are correct. Listed under "p(R|S)" is the probability of reinforcement for a correct response following a short stimulus.

Table 4.2.

Parameter estimates and measures of goodness of fit for the fits of the Weibull function to the cumulative percent correct and bias data of Conditions 2, 4, and 6.

		Discrimination					**Bias**				
Subject	Condition	A	L	S	R^2	RMSE	A	L	S	R^2	RMSE
J107	2	0.73	132.15	0.40	0.99	0.01	0.33	64.24	1.70	0.88	0.03
	4	0.77	290.83	0.30	0.87	0.03	0.32	90.94	0.62	0.77	0.03
	6	0.82	218.66	0.27	0.94	0.02	0.41	151.45	0.46	0.82	0.04
J108	2	0.66	113.72	0.22	0.86	0.02	0.27	221.25	1.54	0.79	0.04
	4	0.79	125.70	0.18	0.71	0.03	0.27	1.57	0.27	-0.45	0.05
	6	0.71	50.00	0.29	0.66	0.05	0.19	200.06	0.32	-0.05	0.07
J109	2	0.82	166.89	0.38	0.99	0.01	0.21	20.94	2.07	0.64	0.03
	4	0.82	166.89	0.38	0.98	0.01	0.36	152.37	1.08	0.86	0.04
	6	0.80	216.35	0.42	1.00	0.01	0.20	119.93	0.61	0.73	0.02

Table 4.3.

Parameter estimates from the fit of the DNA model. Parameter estimates and various indices of goodness of fit for two candidate attending equations (Weibull and Linear-operator) are also listed.

	Weibull						**Lin-op**			
	J107		**J108**		**J109**			**J107**	**J108**	**J109**
d_{s12}	5.03		9.47		2.99		d_{s12}	5.23	9.78	4.04
d_{s23}	16.68		9.65		4.14		d_{s23}	27.07	27.69	4.50
d_{s34}	4.13		2.58		2.73		d_{s34}	5.07	2.94	2.72
d_{s45}	19.00		7.07		22.41		d_{s45}	20.63	28.38	17.27
d_{s56}	19.03		1.00		1.47		d_{s56}	54.93	48.11	1.00
d_r	19.48		19.61		49.94		d_r	49.15	47.06	100.02
bias	1.08		0.84		1.27		bias	1.08	0.87	1.18
	p(A_s)	p(A_c)	p(A_s)	p(A_c)	p(A_s)	p(A_c)				
A	0.69	0.86	1.00	0.56	1.00	0.98	α_{sample}	0.06	0.06	0.90
L	6.37	2.27	5.11	1.79	0.01	1.52	α_{comp}	0.15	0.08	0.23
S	3.33	1.46	2.65	2.40	2.14	0.88				
k	13		13		13		k	9	9	9
AIC	-1185.95		-1312.19		-1391.84		AIC	-1169.90	-1268.85	-1361.59
BIC	-1139.17		-1265.41		-1345.06		BIC	-1137.51	-1236.46	-1329.21
n	270		270		270		n	270	270	270
RMSE	0.11		0.08		0.07		RMSE	0.11	0.09	0.08

		Responses	
		B_1 (yes)	B_2 (no)
Stimuli	S_1 (signal + noise)	*Hit* B_{11} (R_{11})	*Miss* B_{12}
	S_2 (noise)	*False Alarm* B_{21}	*Correct Rejection* B_{22} (R_{22})

Figure 1.1. The 2-stimulus, 2-response signal detection matrix. S_i refers to signal or noise and B_j refers to frequency of response (B_{ij}) in the presence of or following S_i. R_{ij} refers to payoffs or reinforcer frequencies arranged for correct responses. See text for further details.

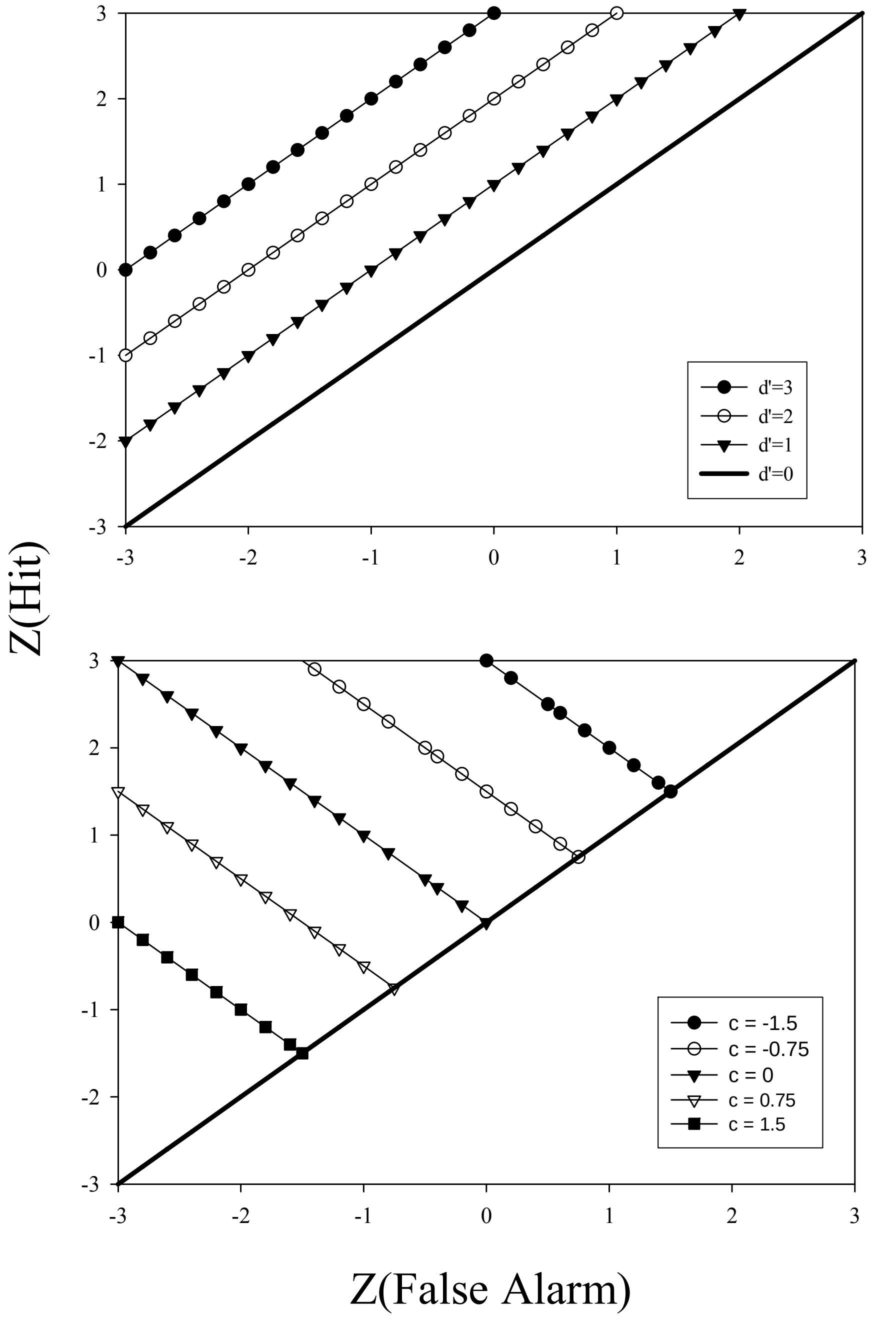

Figure 1.2. Isosensitivity (top) and Isobias (bottom) functions predicted from Equations 1.1 and 1.2. The top graph depicts four levels of sensitivity, given by the measure *d'*. The bottom graph depicts five levels of bias, given by the measure *c*.

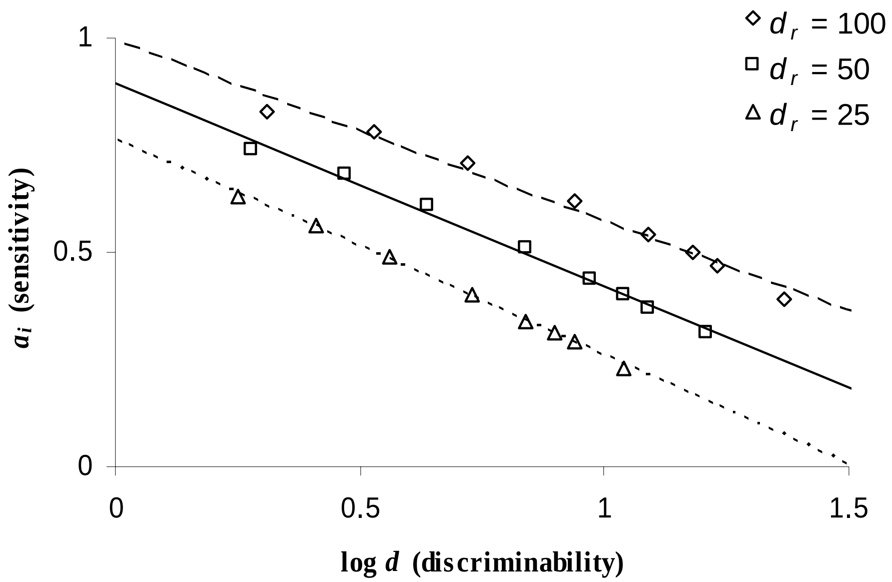

Figure 1.3. Sensitivity to reinforcement (a_r) plotted as a function of stimulus discriminability (log d) obtained from fits of the Davison-Tustin model (1978) to predictions of the model of Alsop and Davison (1991). All discriminabilities were generated assuming a constant level of d_r and d_s varied from 2.5 to 200 according to a geometric series.

Responses **Reinforcers**

Stimuli

$$\begin{array}{c|c|c} & B_1 & B_2 \\ \hline S_1 & B_{11} & B_{12} \\ \hline S_2 & B_{21} & B_{22} \end{array} \qquad \begin{array}{|c|c|} B_1 & B_2 \\ \hline R_{11}+\dfrac{R_{22}}{d_r d_s} & \dfrac{R_{11}}{d_r}+\dfrac{R_{22}}{d_s} \\ \hline \dfrac{R_{11}}{d_s}+\dfrac{R_{22}}{d_r} & \dfrac{R_{11}}{d_r d_s}+R_{22} \end{array}$$

Figure 2.1. Left: The 2-stimulus, 2-response signal detection matrix. S_i refers to the sample presented on a given trial and B_j refers to frequency of response (B_{ij}) in the presence of or following S_i. R_{ij} refers to reinforcer frequencies obtained for correct responses. Right:See text for further details.

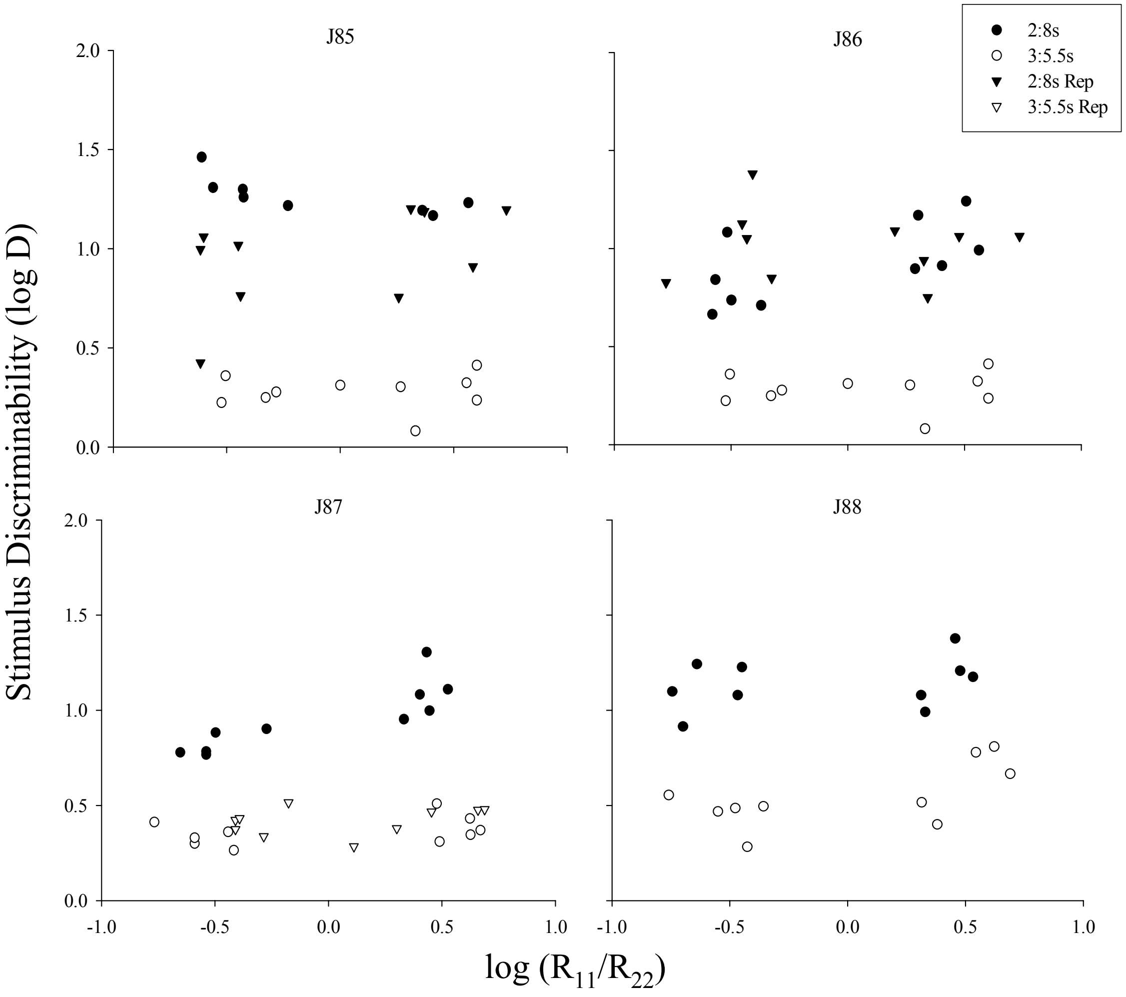

Figure 2.2. Discrimination accuracy expressed as log D (Eq. 3) as a function of obtained sessional reinforcer ratio. Estimates of log D are presented for each subject for the last ten sessions at each reinforcer ratio for each condition of Experiment 1.

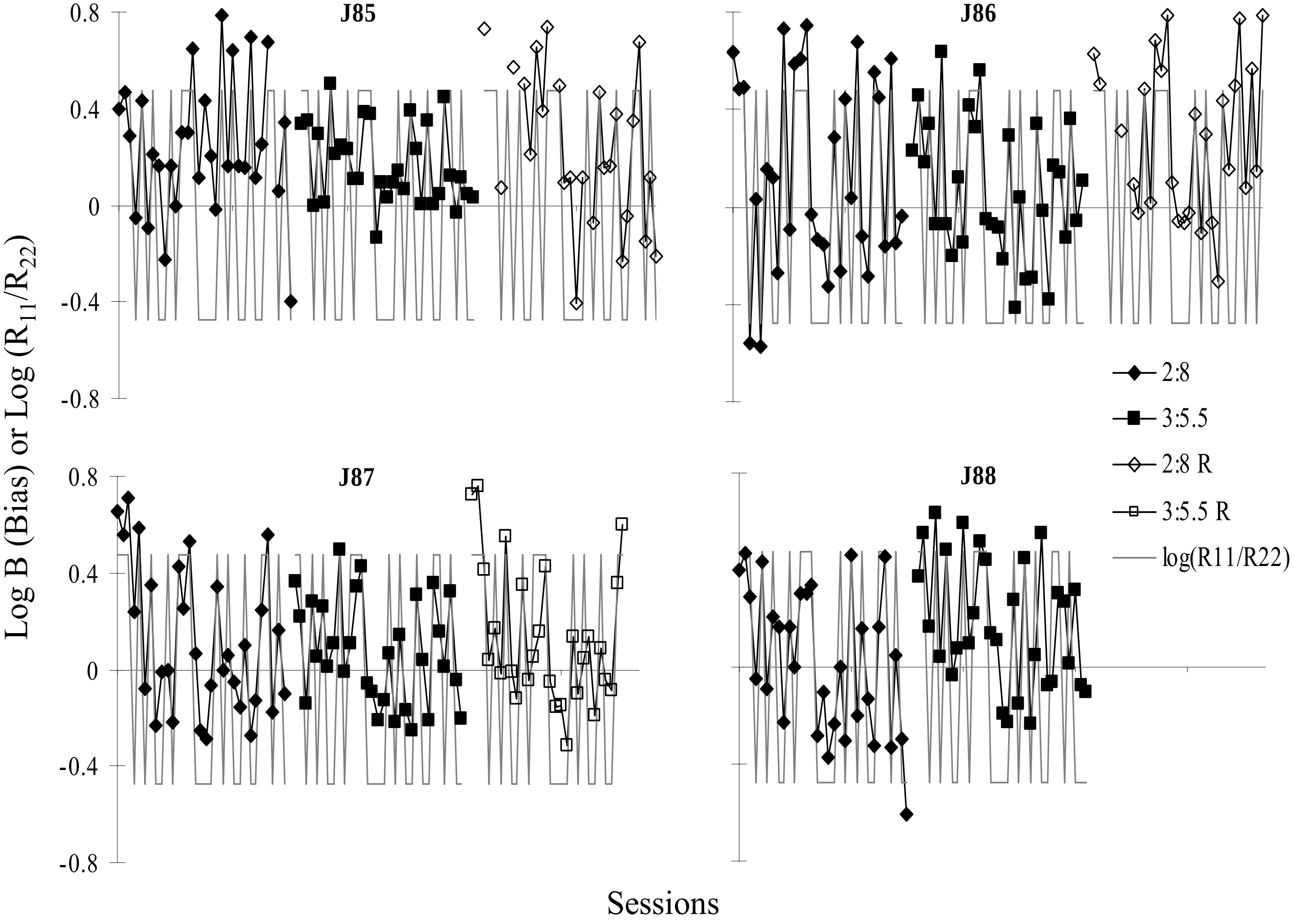

Figure 2.3. Response bias (heavy lines, filled symbols), expressed as log B (Eq. 4), and log R (R_{11}/R_{22}), the programmed reinforcer frequency ratio (light lines) as a function of session number for PRBS presentations completed by each subject. See text for further explanation of individual subject condition order.

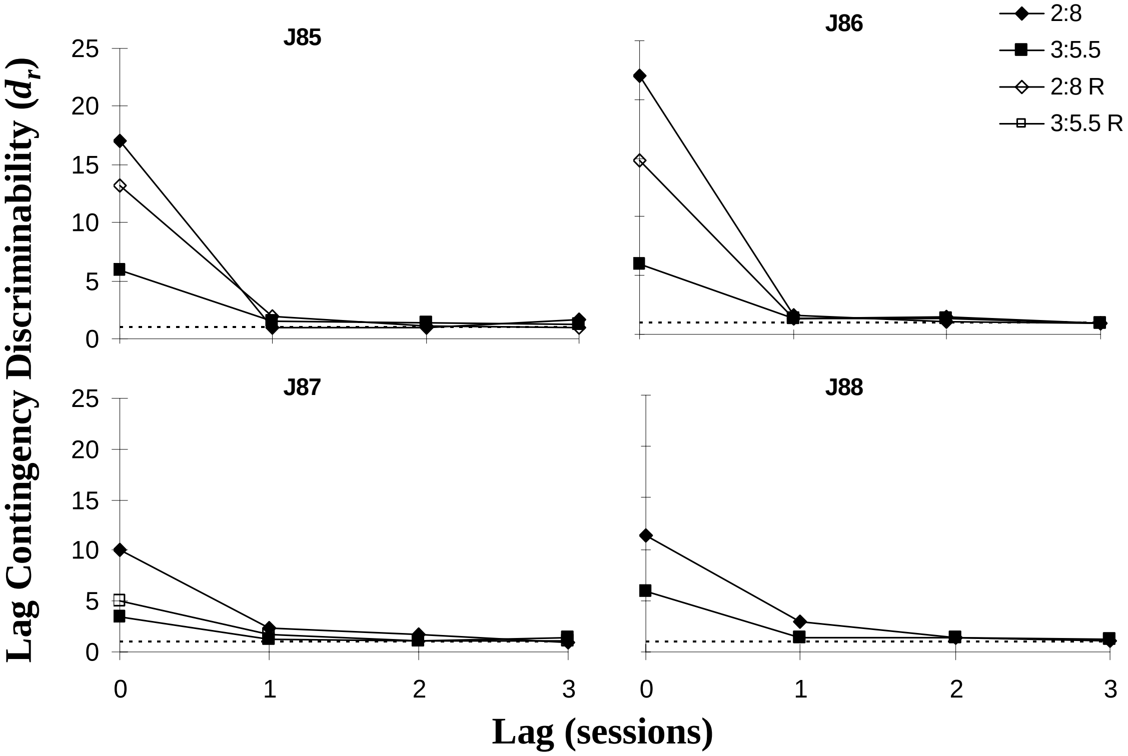

Figure2. 4. Contingency discriminability to current and previous session reinforcer ratios for each PRBS presentation of Experiment 1. The legend indicates the PRBS presentation from which the d_{br12} estimate was obtained. The dotted lines across the bottom of the graphs show the lower limit of the parameter value. Conditions are labeled according to sample stimulus durations, R indicates a replication.

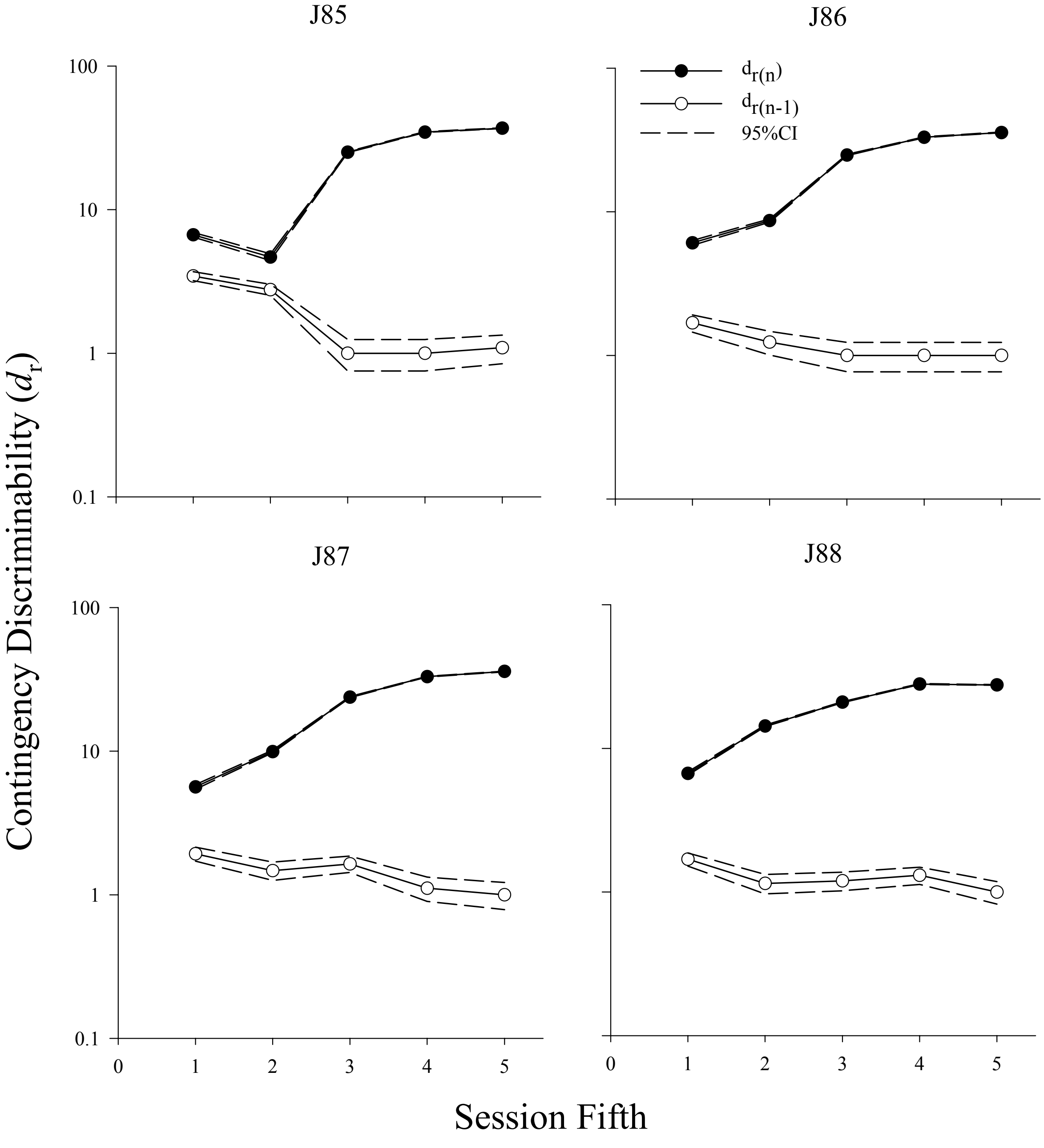

Figure 2.5. Contingency discriminability d_r obtained for lags 0 through 1obtained for each session fifth (30 trials). Data are from the first PRBS with 2- and 8-s sample stimuli of Experiment 1.

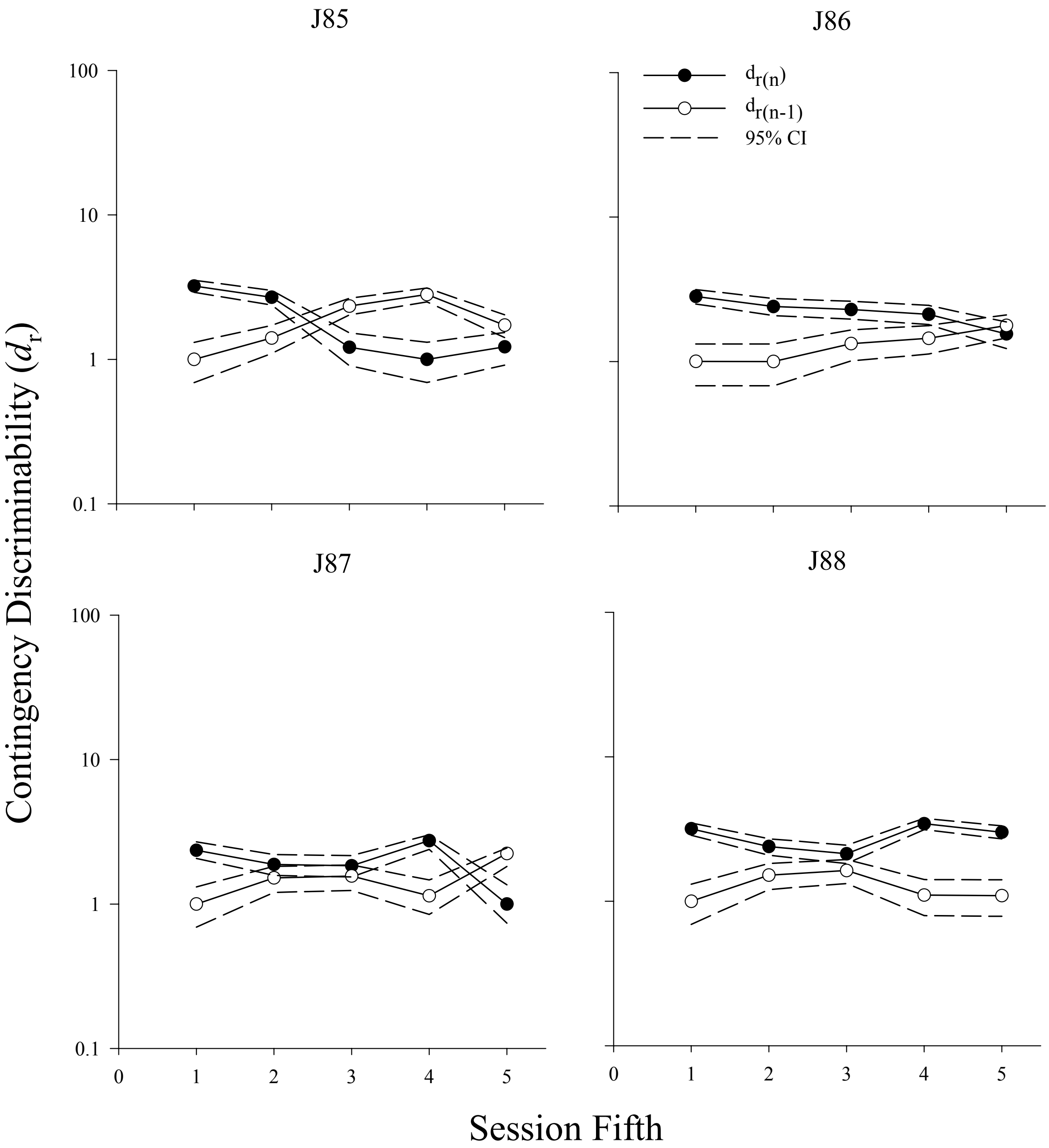

Figure 2.6. Contingency discriminability d_r obtained for lags 0 through 1obtained for each session fifth (30 trials). Data are from the second PRBS with 3- and 5.5-s sample stimuli of Experiment 1.

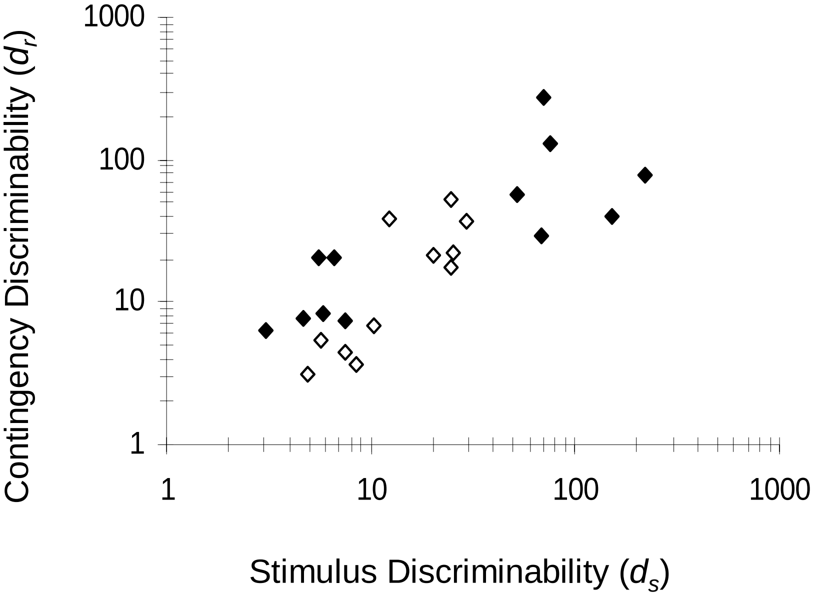

Figure 2.7. Estimates of contingency discriminability (d_r) plotted as a function of stimulus discriminability (d_s) from fits of the DNA detection model. The filled symbols are parameter estimates obtained from fits to the data of McCarthy and Davison (1980). The open symbols are parameter estimates obtained in the present study. Note double logarithmic axes.

	B_1	B_2
S_1	$R_{11}+\frac{R_{21}}{d_{s12}}+\frac{R_{32}}{d_{s13}d_{r12}}+\frac{R_{42}}{d_{s14}d_{r12}}$	$\frac{R_{11}}{d_{r12}}+\frac{R_{21}}{d_{s12}d_{r12}}+\frac{R_{32}}{d_{s13}}+\frac{R_{42}}{d_{s14}}$
S_2	$\frac{R_{11}}{d_{s12}}+R_{21}+\frac{R_{32}}{d_{s23}d_{r12}}+\frac{R_{42}}{d_{s24}d_{r12}}$	$\frac{R_{11}}{d_{s12}d_{r12}}+\frac{R_{21}}{d_{r12}}+\frac{R_{32}}{d_{s23}}+\frac{R_{42}}{d_{s24}}$
S_3	$\frac{R_{11}}{d_{s13}}+\frac{R_{21}}{d_{s23}}+\frac{R_{32}}{d_{r12}}+\frac{R_{42}}{d_{s34}d_{r12}}$	$\frac{R_{11}}{d_{s13}d_{r12}}+\frac{R_{21}}{d_{s23}d_{r12}}+R_{32}+\frac{R_{42}}{d_{s34}}$
S_4	$\frac{R_{11}}{d_{s14}}+\frac{R_{21}}{d_{s24}}+\frac{R_{32}}{d_{s34}d_{r12}}+\frac{R_{42}}{d_{r12}}$	$\frac{R_{11}}{d_{s14}d_{r12}}+\frac{R_{21}}{d_{s24}d_{r12}}+\frac{R_{32}}{d_{s34}}+R_{42}$

Figure 3.1. The effective reinforcer allocation for the eight cells of the 4x2 signal detection matrix for a 4-stimulus, 2-response detection procedure assuming reinforcers for correct responses only.

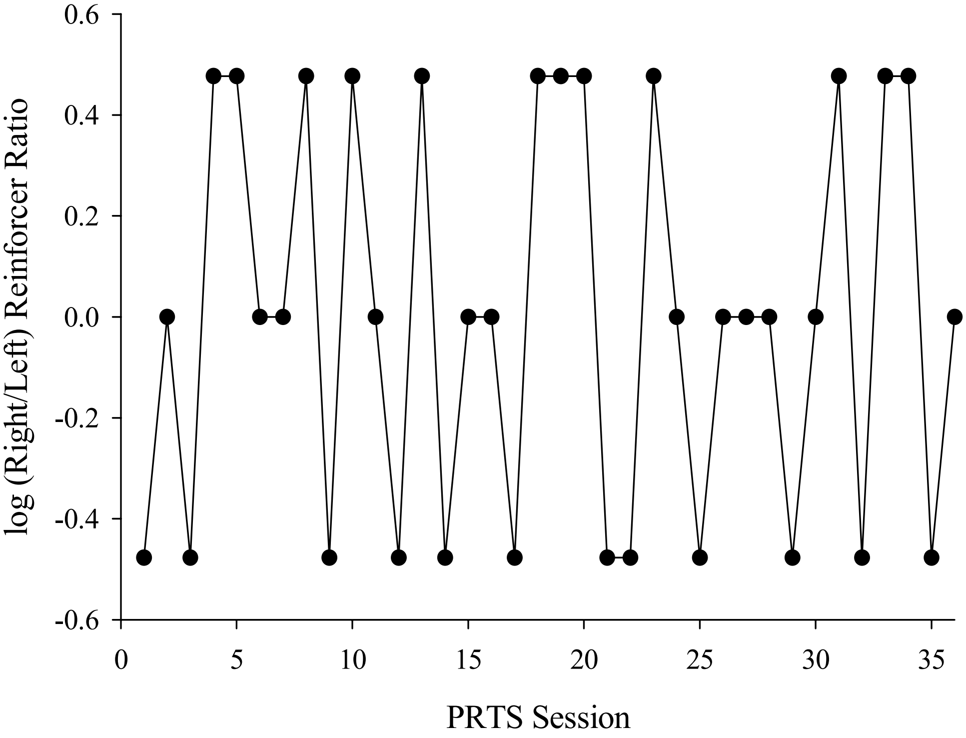

Figure 3.2. Programmed reinforcer frequency ratios for each of the 36 sessions of the PRTS.

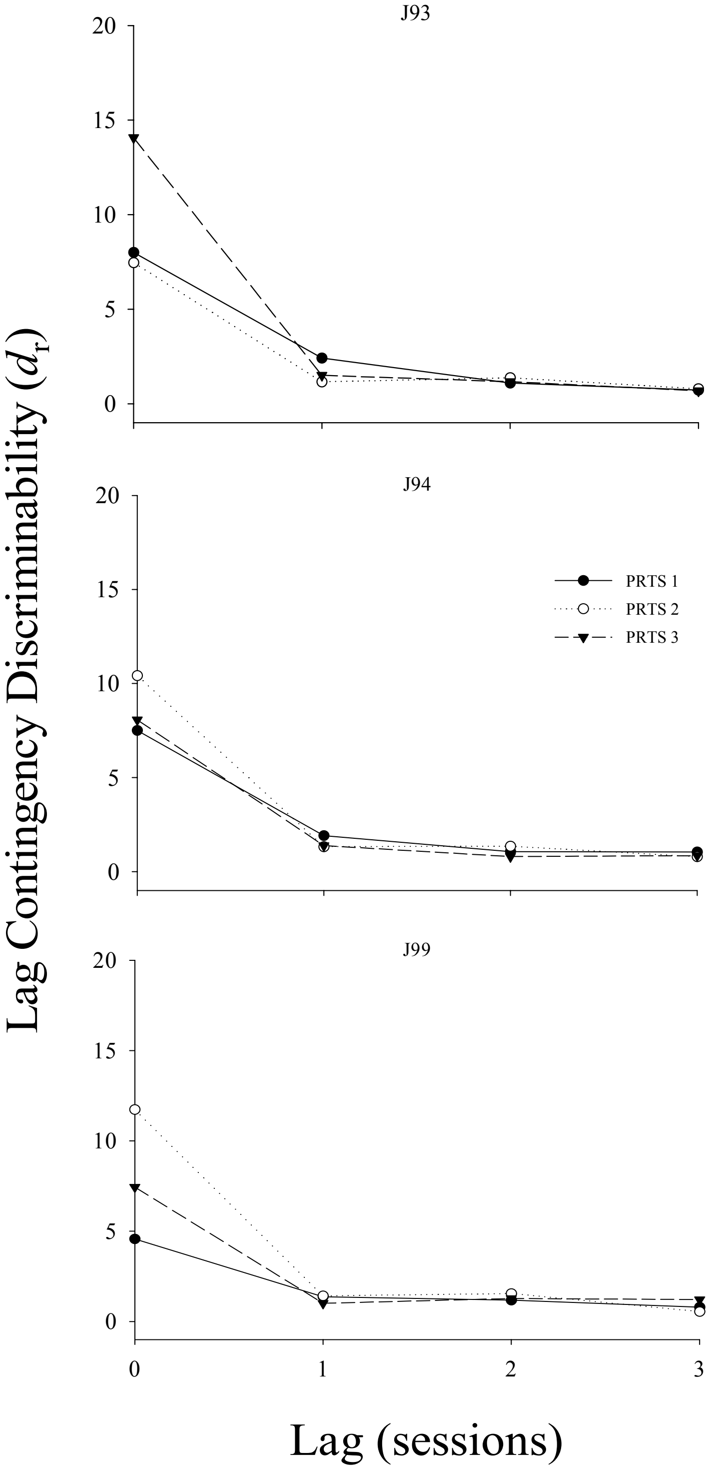

Figure 3.3. Contingency discriminability d_r to current and previous session reinforcer ratios for each PRTS presentation. The legend indicates the PRTS presentation from which the d_{r12} estimate was obtained. The dotted lines give the lower limit of the parameter value.

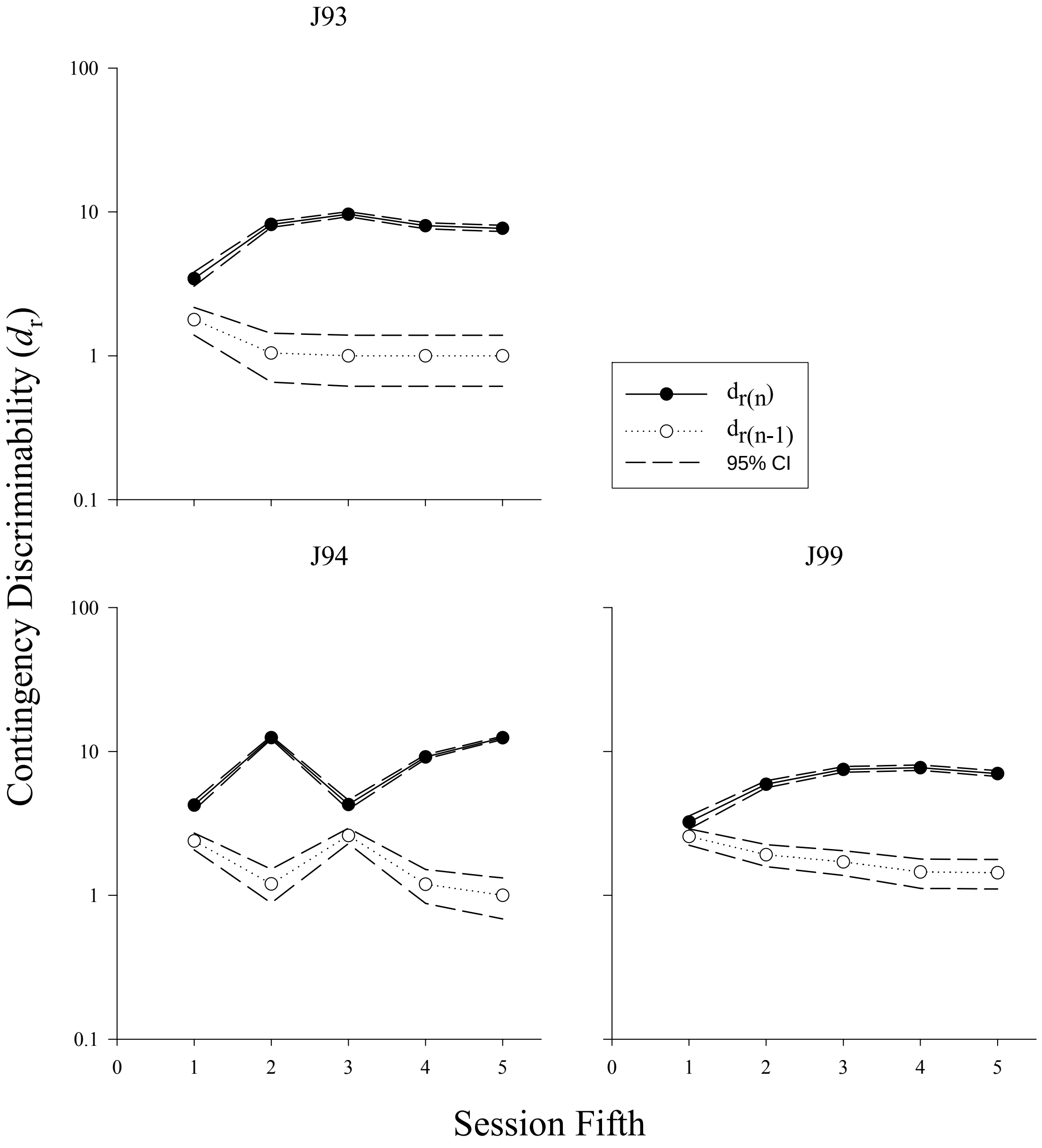

Figure 3.4. Contingency discriminability d_r obtained for lags 0 and 1 obtained for each session fifth (40 trials). Data are from the third PRTS presentation of Experiment 2. *Figure 3.5.* Psychometric functions based on the data from the last two trial blocks of each session from the third PRTS. The proportion of long responses following each stimulus duration is plotted separately for each programmed reinforcer frequency ratio as indicated in the legend. Vertical bars represent standard error.

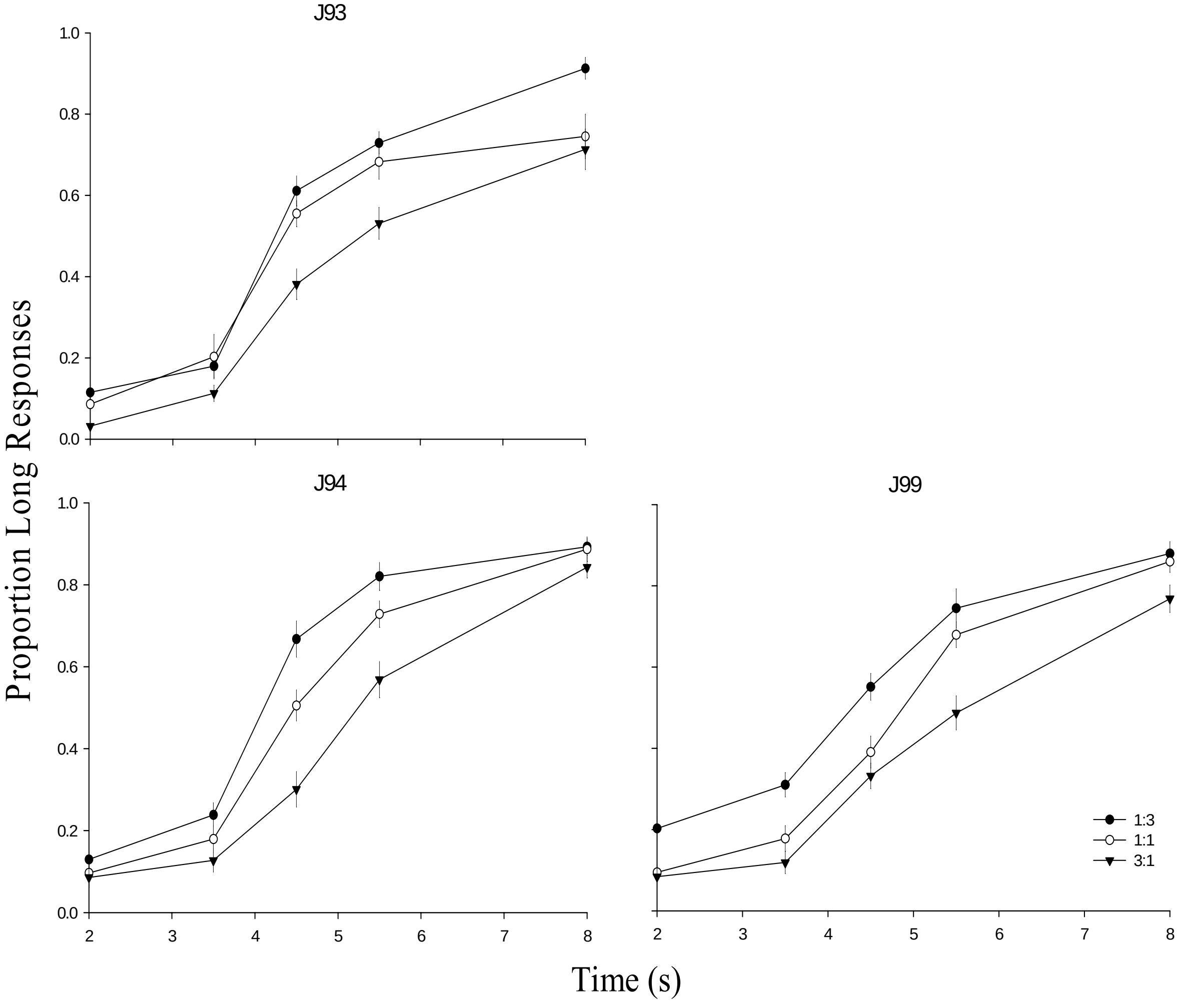

Figure 3.5. Psychometric functions based on the data from the last two trial blocks of each session from the third PRTS. The proportion of long responses following each stimulus duration is plotted separately for each programmed reinforcer frequency ratio as indicated in the legend. Vertical bars represent standard error.

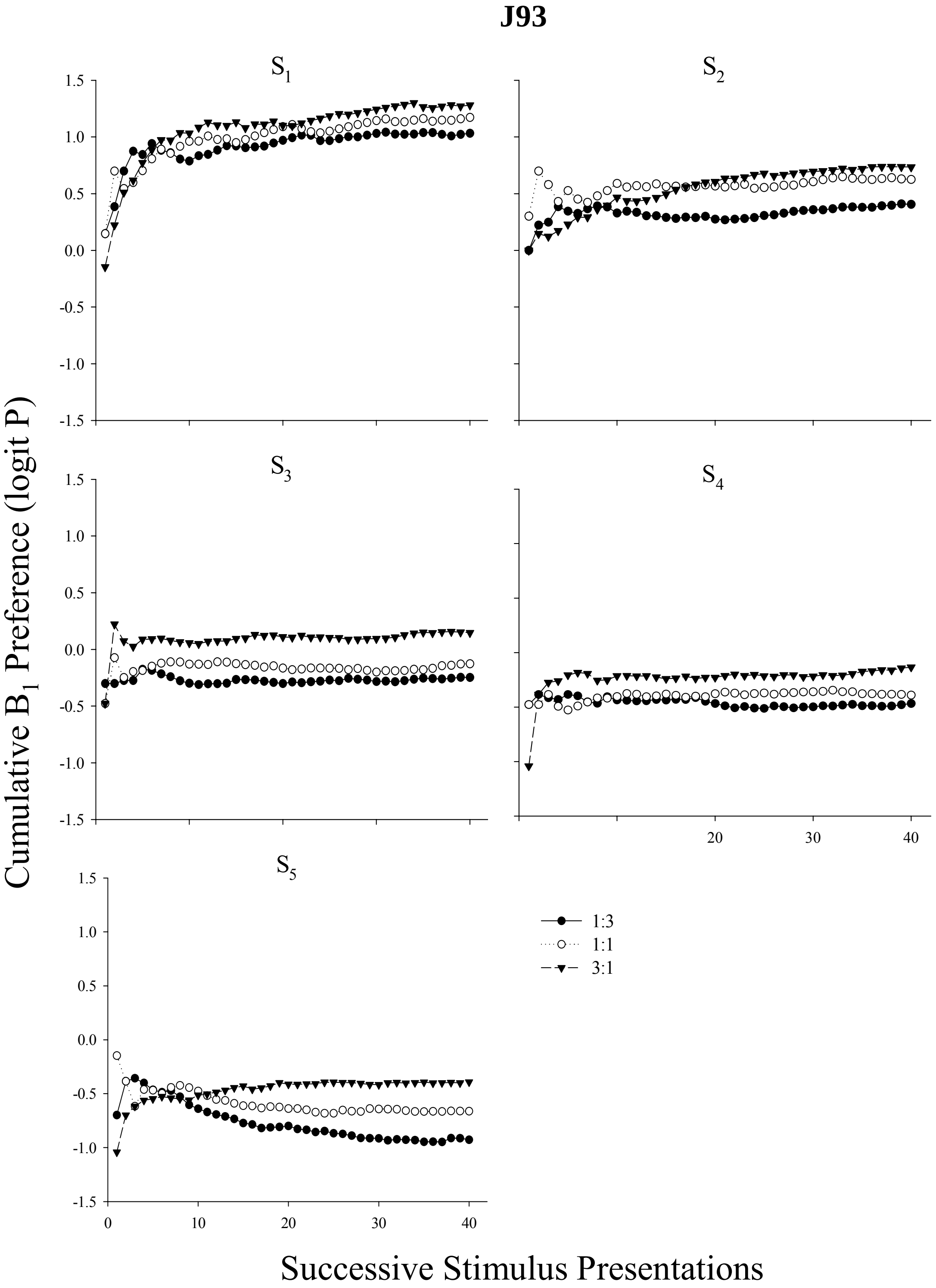

Figure 3.6. The cumulative response ratio following each sample stimulus transformed to logit *p* and plotted as a function of successive presentations of each sample stimulus S_i. Data are aggregated across each session of a given reinforcer ratio (indicated in the legend) from the third PRTS for subject J93.

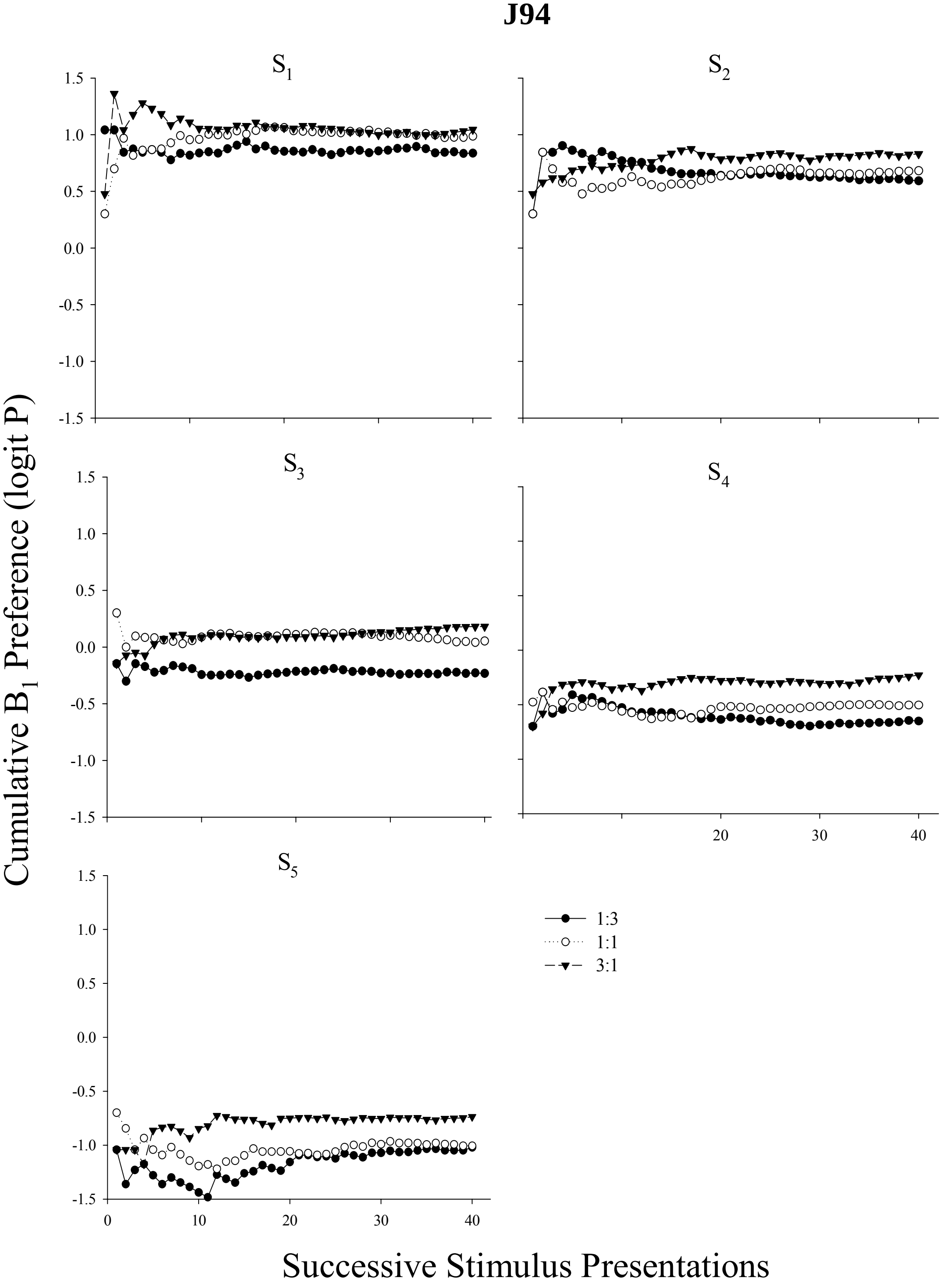

Figure 3.7. The cumulative response ratio following each sample stimulus transformed to logit *p* and plotted as a function of successive presentations of each sample stimulus S_i. Data are aggregated across each session of a given reinforcer ratio (indicated in the legend) from the third PRTS for subject J94.

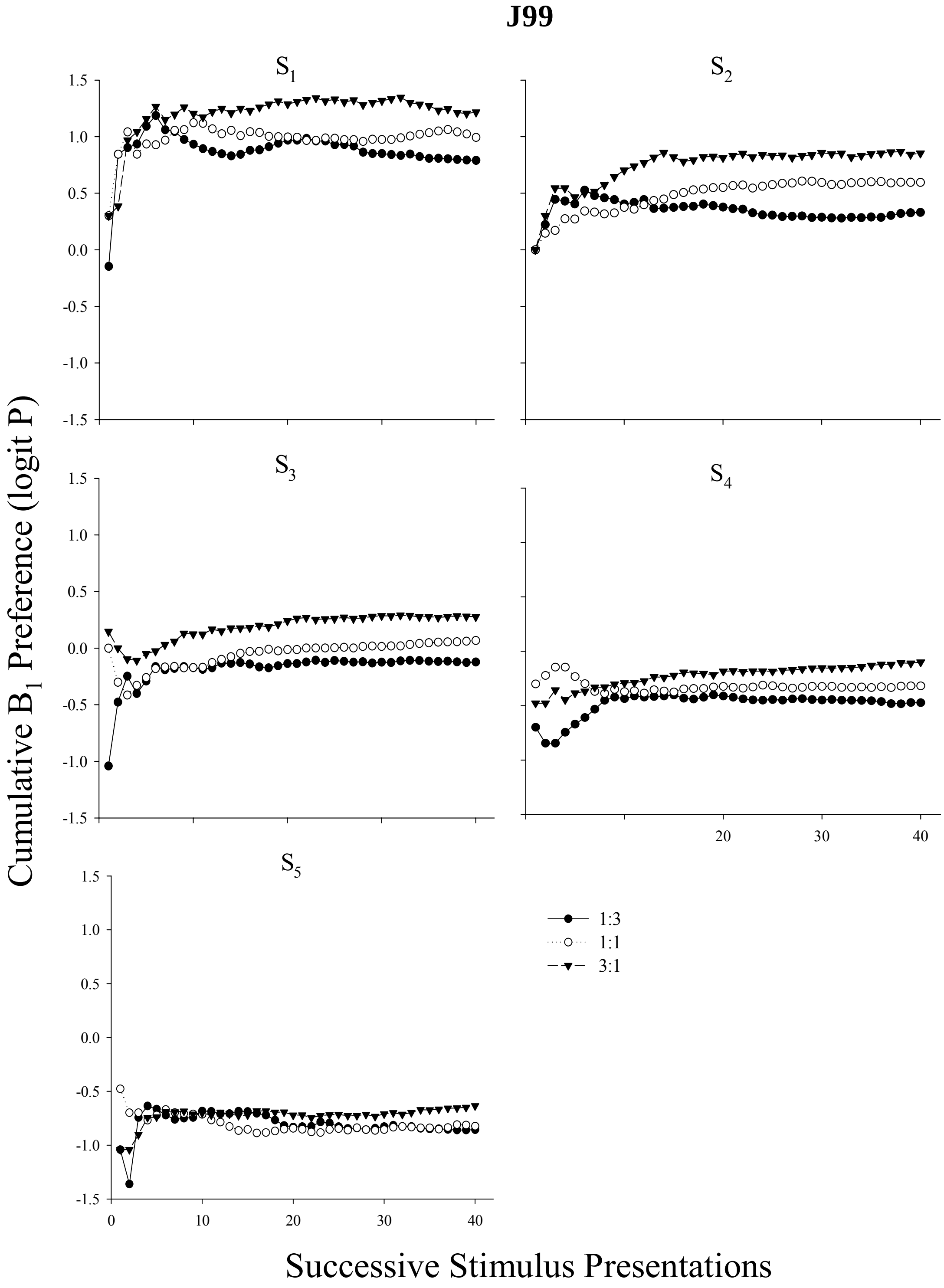

Figure 3.8. The cumulative response ratio following each sample stimulus transformed to logit *p* and plotted as a function of successive presentations of each sample stimulus S_i. Data are aggregated across each session of a given reinforcer ratio (indicated in the legend) from the third PRTS for subject J99.

	B$_1$	**B$_2$**
S$_1$	$R_{11} + \frac{R_{22}}{d_s\, d_r}$	$\frac{R_{11}}{d_r} + \frac{R_{22}}{d_s}$
S$_2$	$\frac{R_{11}}{d_s} + \frac{R_{22}}{d_r}$	$R_{22} + \frac{R_{11}}{d_s d_r}$

Figure 4.1. Above: the basic 2x2 detection matrix, cells are designated by row-column notation. Below: the effective reinforcer allocation for the four cells of the 2x2 signal detection matrix, assuming reinforcers for correct responses according to the model of Alsop and Davison (1991).

Attend to sample & comparisons

$$p\langle B1|S1\rangle = \frac{R_{11}+\frac{R_{22}}{d_s d_r}}{\left(R_{11}+\frac{R_{22}}{d_s d_r}\right)+\left(\frac{R_{11}}{d_r}+\frac{R_{22}}{d_s}\right)}$$

State 1 :
$p(A_s)\cdot p(A_c)$

$$p\langle B1|S2\rangle = \frac{\frac{R_{11}}{d_s}+\frac{R_{22}}{d_r}}{\left(\frac{R_{11}}{d_s}+\frac{R_{22}}{d_r}\right)+\left(\frac{R_{11}}{d_s d_r}+R_{22}\right)}$$

Attend to sample but not comparisons

$$p\langle B1|S1\rangle = \frac{R_{11}+\frac{R_{22}}{d_s}}{\left(R_{11}+\frac{R_{22}}{d_s}\right)+\left(R_{11}+\frac{R_{22}}{d_s}\right)} = 0.5$$

State 2 :
$p(A_s)\cdot((1-p(A_c))$

$$p\langle B1|S2\rangle = \frac{\frac{R_{11}}{d_s}+R_{22}}{\left(\frac{R_{11}}{d_s}+R_{22}\right)+\left(\frac{R_{11}}{d_s}+R_{22}\right)} = 0.5$$

Attend to comparisons but not sample

$$p\langle B1|S1\rangle = \frac{R_{11}+\frac{R_{22}}{d_r}}{\left(R_{11}+\frac{R_{22}}{d_r}\right)+\left(R_{11}+\frac{R_{22}}{d_s}\right)}$$

State 3 :
$((1-p(A_s))\cdot p(A_c))$

$$p\langle B1|S2\rangle = \frac{R_{11}+\frac{R_{22}}{d_r}}{\left(R_{11}+\frac{R_{22}}{d_r}\right)+\left(\frac{R_{11}}{d_r}+R_{22}\right)}$$

Do not attend to sample or comparisons

$$p\langle B1|S1\rangle = \frac{R_{11}+R_{22}}{(R_{11}+R_{22})+(R_{11}+R_{22})} = 0.5$$

State 4 :
$((1-p(A_s))\cdot((1-p(A_c))$

$$p\langle B1|S2\rangle = \frac{R_{11}+R_{22}}{(R_{11}+R_{22})+(R_{11}+R_{22})} = 0.5$$

Figure 4.2. The equations of the model of Davison and Nevin (1999) modified by the probabilities of attention to the sample stimulus and attention (State 1) or inattention (State 2) to the comparison stimuli; inattention to the sample stimulus and attention (State 3) or inattention (State 4) to the comparison stimuli

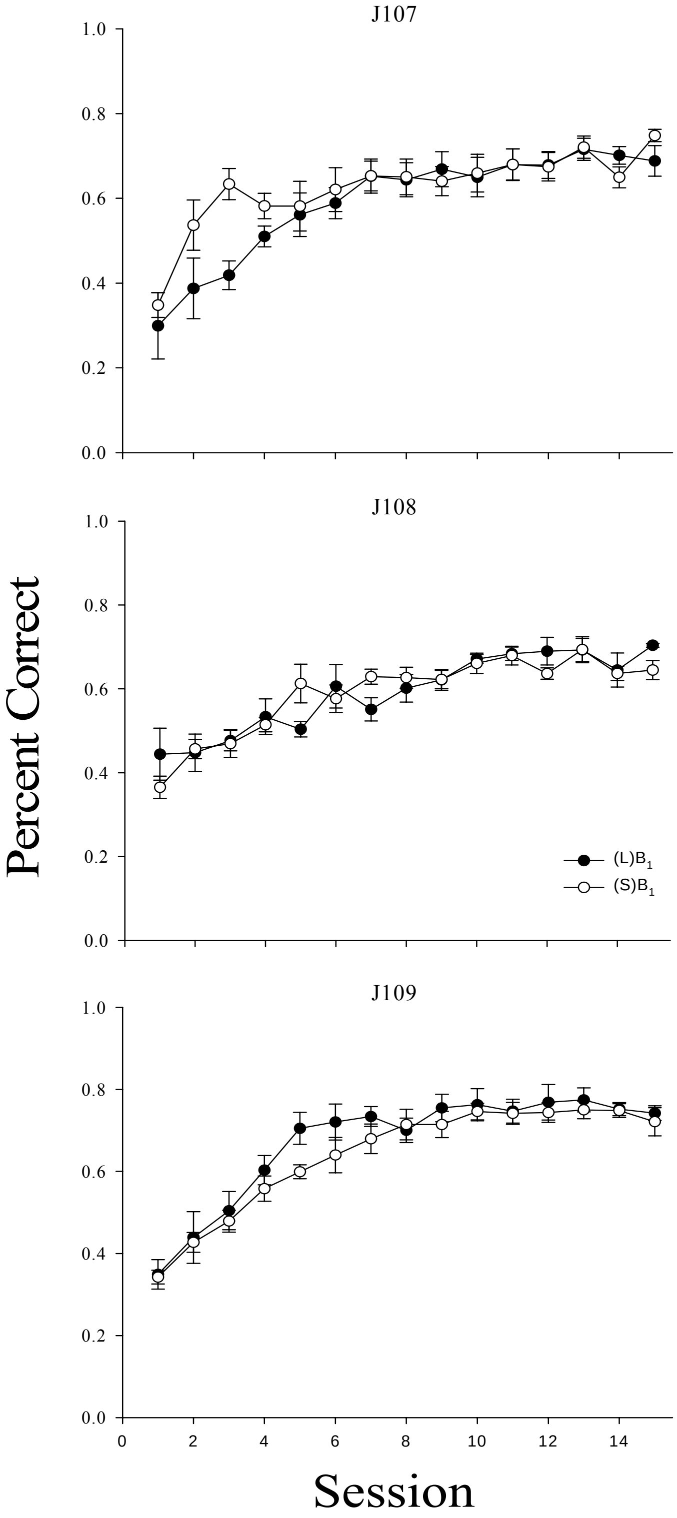

Figure 4.3. Percent correct plotted as a function of session for each subject. The correct comparison given a short stimulus duration is indicated in the legend. The data were averaged across the last three reversals for each subject. Vertical bars represent standard error.

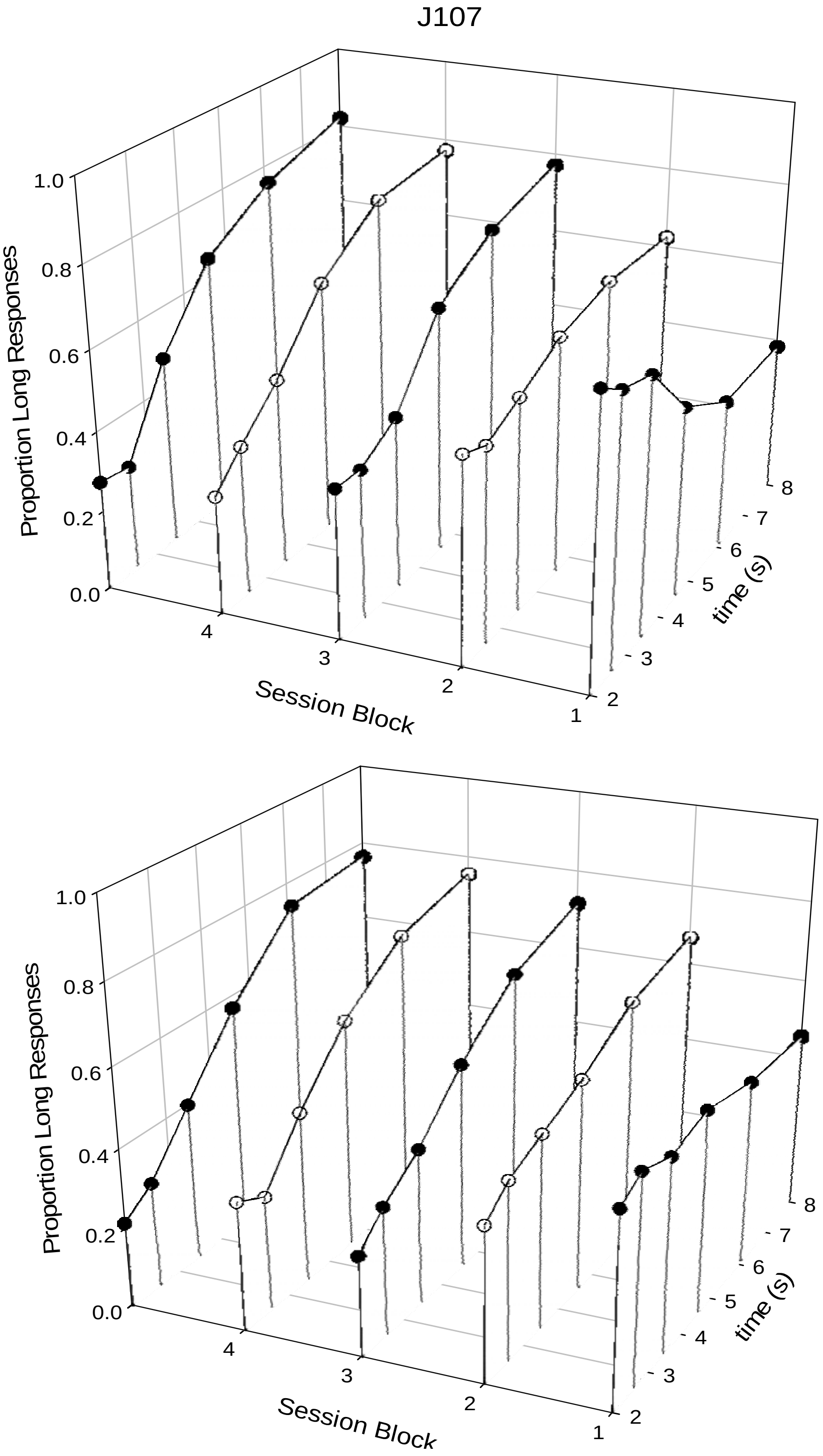

Figure 4.4. Psychometric functions plotting the proportion of long responses as a function of sample stimulus duration and session block for subject J107. The upper plots come from sessions in which B_1 was correct following short stimulus durations and the lower plots from sessions in which B_2 was correct following short stimulus durations.

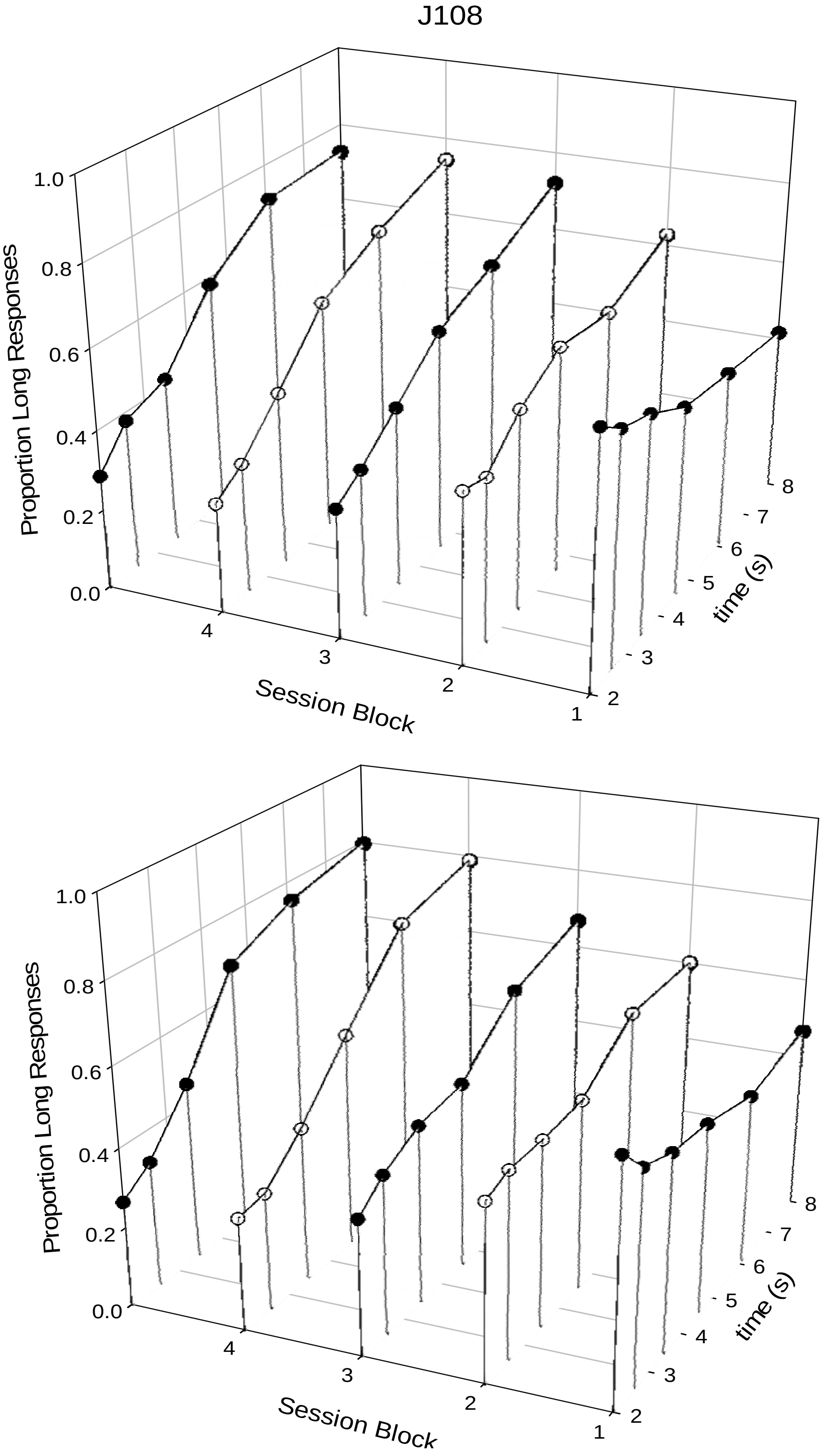

Figure 4.5. Psychometric functions plotting the proportion of long responses as a function of sample stimulus duration and session block for subject J108. The upper plots come from sessions in which B_1 was correct following short stimulus durations and the lower plots from sessions in which B_1 was correct following long stimulus durations.

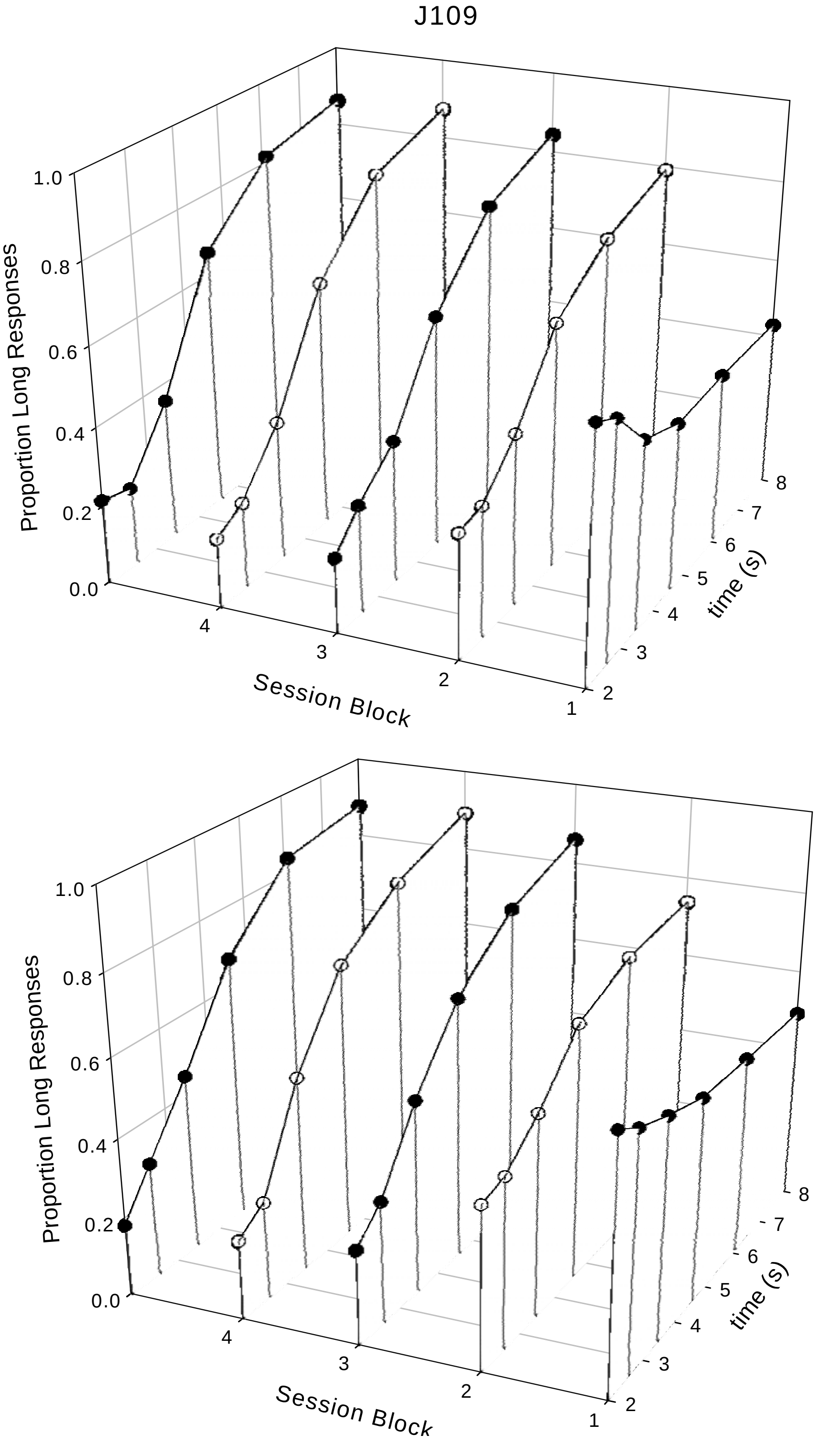

Figure 4.6. Psychometric functions plotting the proportion of long responses as a function of sample stimulus duration and session block for subject J109. The upper plots come from sessions in which B_1 was correct following short stimulus durations and the lower plots from sessions in which B_1 was correct following long stimulus durations.

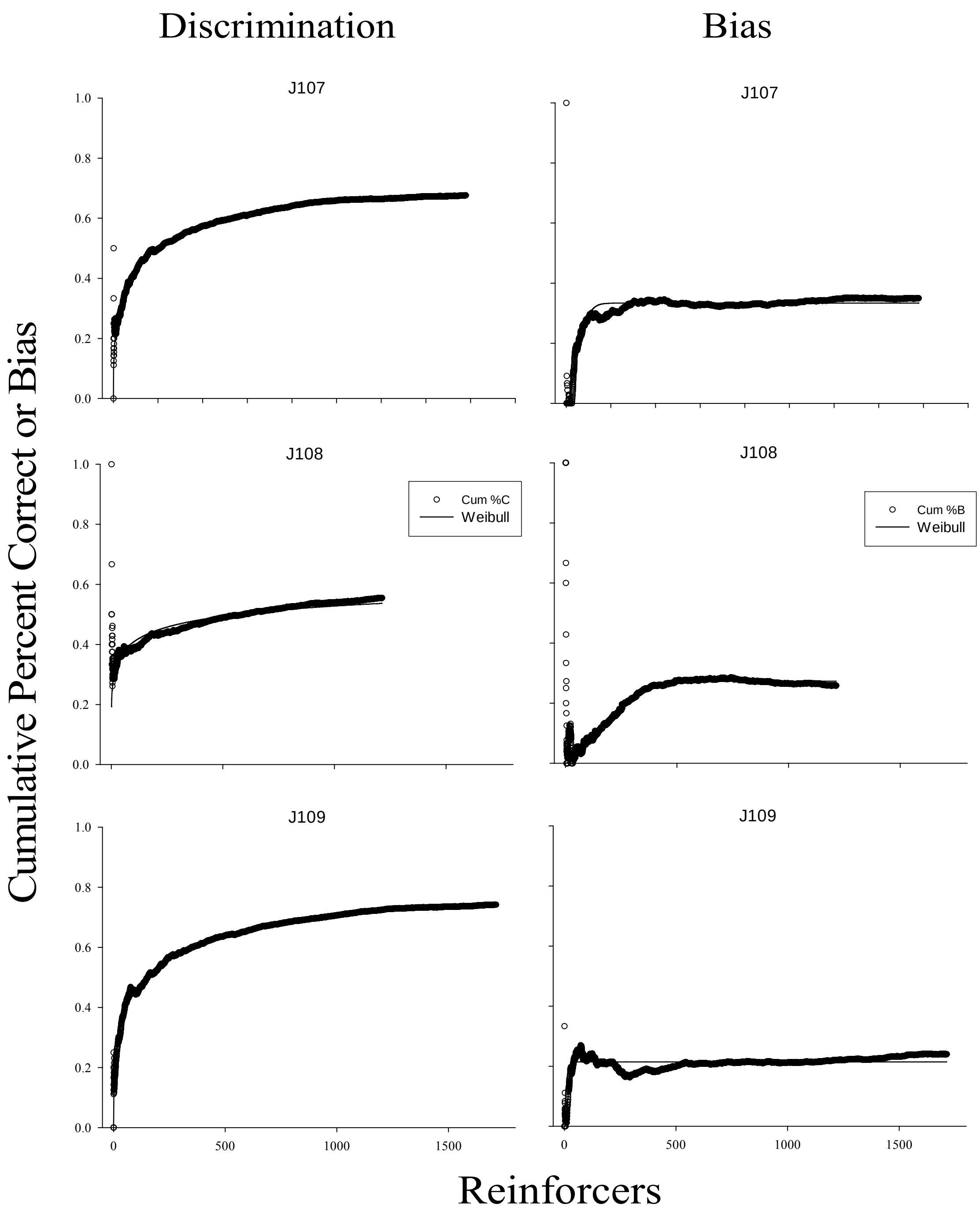

Figure 4.7. The cumulative percentage of correct responses (left panel) and percent of responses to the higher frequency reinforcer alternative (right panel) plotted as a function of cumulative reinforcers earned. The data come from Condition 2. Thin lines are best fitting Weibull functions to the obtained data.

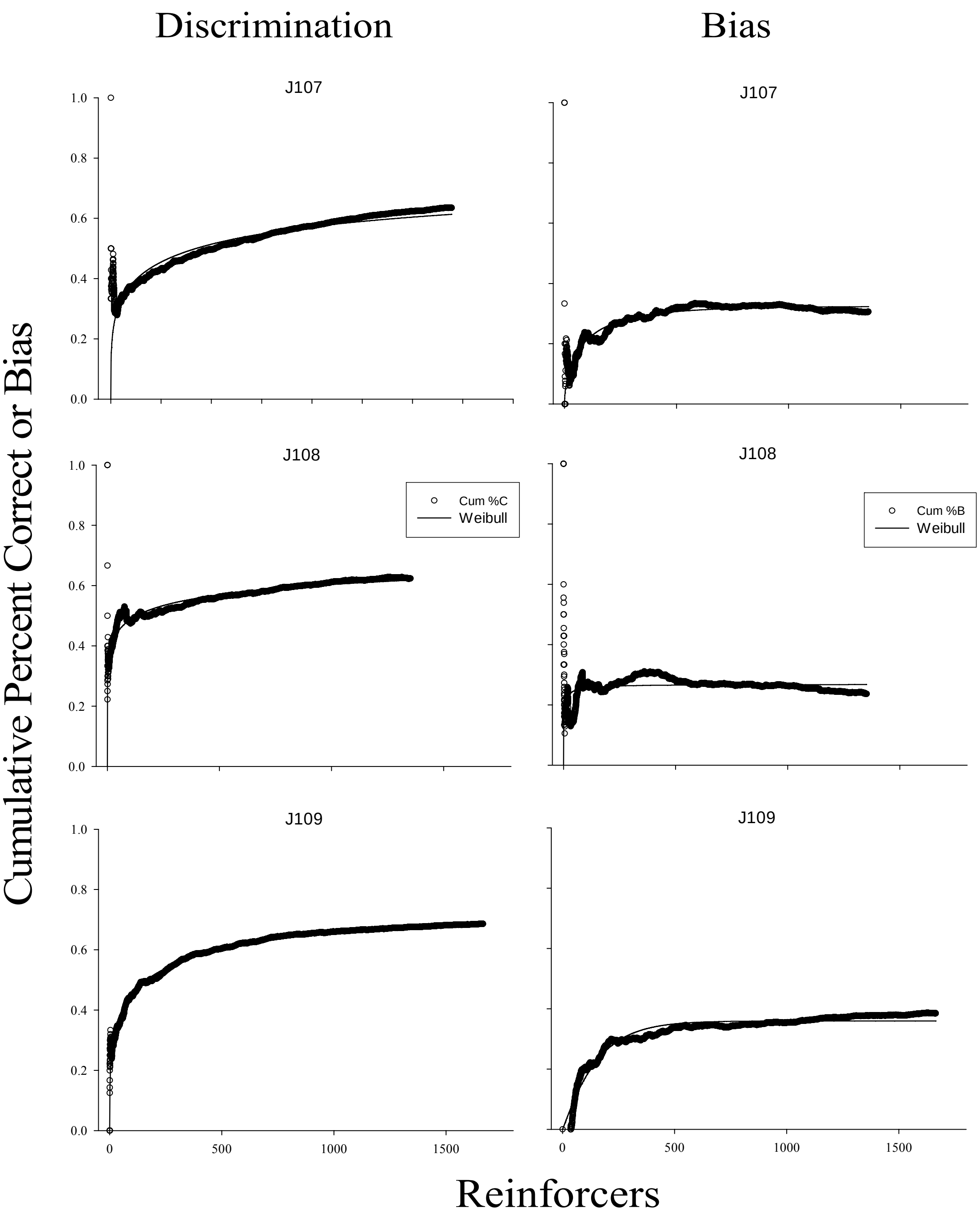

Figure 4.8. The cumulative percentage of correct responses (left panel) and percent of responses to the higher frequency reinforcer alternative (right panel) plotted as a function of cumulative reinforcers earned. The data come from Condition 4. Thin lines are best fitting Weibull functions to the obtained data.

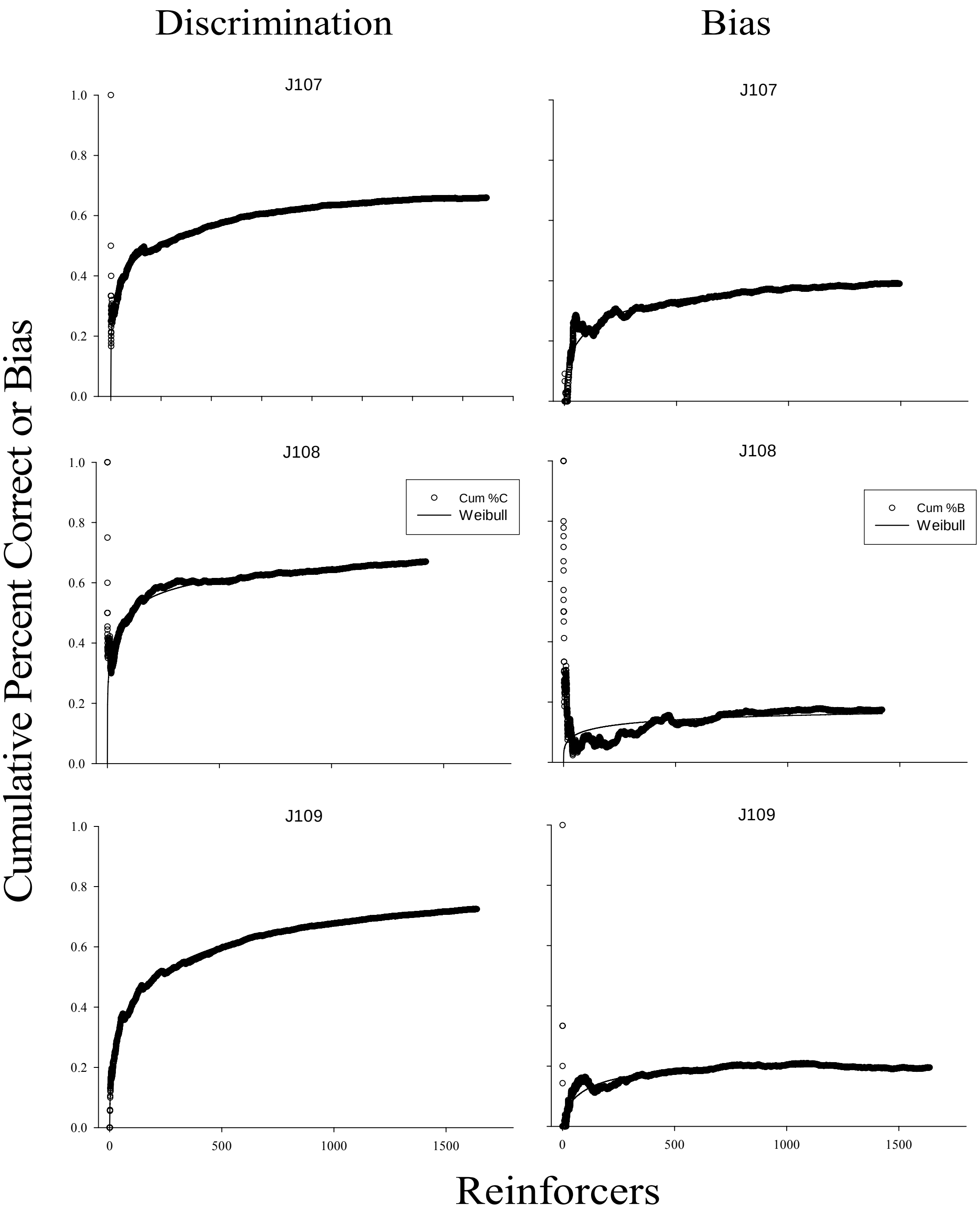

Figure 4.9. The cumulative percentage of correct responses (left panel) and percent of responses to the higher frequency reinforcer alternative (right panel) plotted as a function of cumulative reinforcers earned. The data come from Condition 6. Thin lines are best fitting Weibull functions to the obtained data.

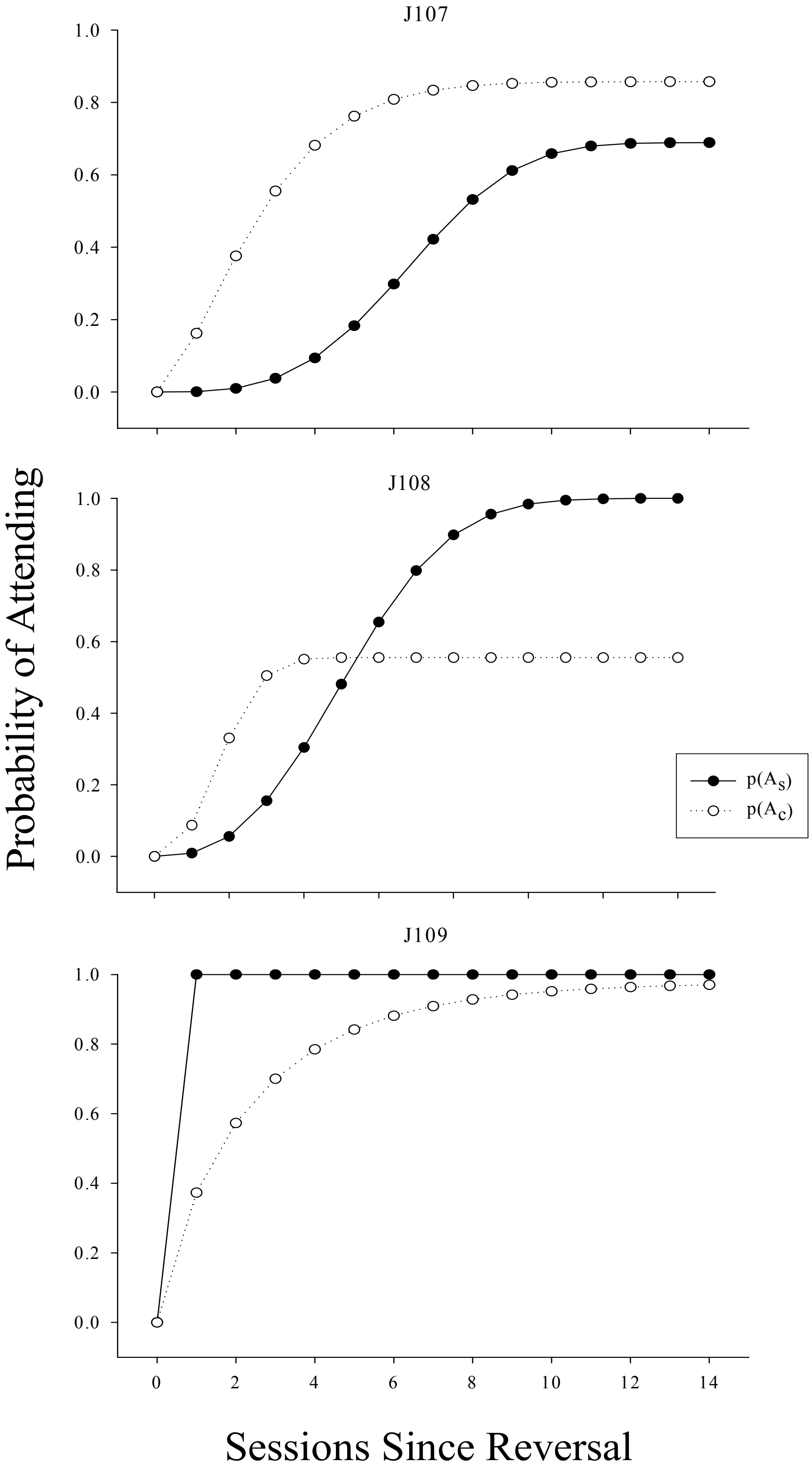

Figure 4.10. The probabilities of attending to the sample and comparison stimuli according the best fitting Weibull function to each subjects' data. See text for further explanation.

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