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EFFECTS OF POINT-LOSS PUNISHERS ON HUMAN SIGNAL-DETECTION PERFORMANCE

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Three experiments using human participants varied the distribution of point-gain reinforcers or point-loss punishers in two-alternative signal-detection procedures. Experiment 1 varied the distribution of point-gain reinforcers for correct responses (Group A) and point-loss punishers for errors (Group B) across conditions. Response bias varied systematically as a function of the relative reinforcer or punisher frequencies. Experiment 2 arranged two conditions – one where an unequal ratio of reinforcement (5:1 or 1:5) was presented without punishment (R-only), and another where the same reinforcer ratio was presented with an equal distribution of point-loss punishers (R+P). Response bias was significantly greater in the R-only condition than the R+P condition, supporting a subtractive model of punishment. Experiment 3 varied the distribution of point-gain reinforcers for correct responses across four unequal reinforcer ratios (5:1, 2:1, 1:2, 1:5) both without (R-only) and with (R+P) an equal distribution of point-loss punishers for errors. Response bias varied systematically with changes in relative reinforcer frequency for both R-only and R+P conditions, with 5 out of 8 participants showing increases in sensitivity estimates from R-only to R+P conditions. Overall, the results indicated that punishers have similar but opposite effects to reinforcers in detection procedures and that combined reinforcer and punisher effects might be better modeled by a subtractive punishment model than an additive punishment model, consistent with research using concurrent-schedule choice procedures.

Key words: punishment, point-loss, signal detection, mouse-click, humans

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Many situations require organisms to discriminate between stimuli that signal different consequences. For example, a bee must decide whether a plant's pollen is toxic or safe, or a pedestrian must decide whether or not it is safe to cross the road. In these examples, both the positive consequences arising from correct choices and the negative consequences arising from errors affect the choices that are made.

Signal-detection tasks (also known as conditional discriminations) are often used to study choice and stimulus discriminability. This is a discrete-trial procedure where, on each trial, the subject is presented with one of two discriminative stimuli (S_1 or S_2) that vary on some dimension (e.g., intensity or color). The subject then chooses between two response alternatives (B_1 or B_2), where B_1 is the correct response following an S_1 presentation, and B_2 is the correct response following an S_2 presentation. B_1 and B_2 are usually physical responses, such as left or right key pecks or lever presses. With two stimulus types (S_1 and S_2) and two response options (B_1 and B_2), there are four possible response outcomes (Figure 1): B_{11} (responding B_1 following S_1)—a correct response, B_{12} (responding B_2 following S_1)—an error, B_{21} (responding B_1 following S_2)—an error, and B_{22} (responding B_2 following S_2)—a correct response. Often, correct responses (B_{11} and B_{22}) are reinforced (e.g., money: Johnstone & Alsop, 2000; food: McCarthy & Davison, 1979; brain stimulation: Terman, 1970) while errors (B_{12} and B_{21}) have no consequence.

Behavioral models of signal-detection performance (e.g., Alsop, 1991; Davison, 1991; Davison & Nevin, 1999; Davison & Tustin, 1978) arose from the generalized matching law (GML: Baum, 1974) which describes how behavior is allocated across two concurrently available response alternatives when each alternative is associated with its own schedule of reinforcement. The GML can be written

$$\log\left(\frac{B_1}{B_2}\right) = a\log\left(\frac{R_1}{R_2}\right) + \log c, \qquad (1)$$

where B_1 and B_2 are the number of responses made on Alternatives 1 and 2 respectively, and R_1 and R_2 are the numbers of obtained reinforcers for B_1 and B_2 responses respective-

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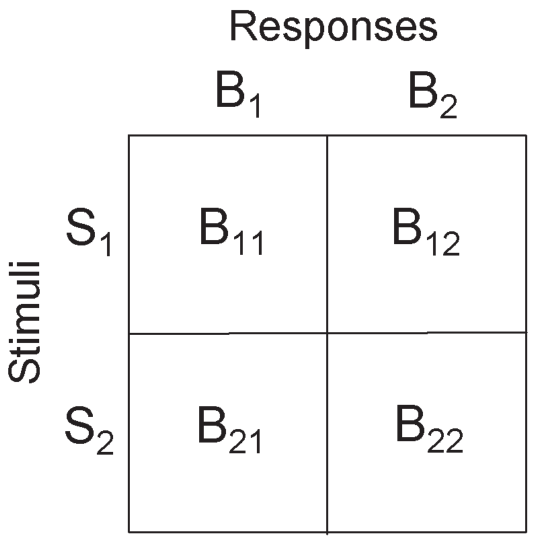

Fig. 1. A 2 × 2 matrix illustrating the four possible response outcomes in a two-alternative signal-detection task.

ly. Equation 1 is in the form of a straight line with slope a and intercept of log c. The parameter a is the sensitivity of the subject's behavior to the distribution of reinforcers, and measures the extent to which changes in the reinforcer distribution (R_1/R_2) produce changes in the response distribution (B_1/B_2). The parameter log c measures any inherent bias in the subject's behavior towards making B_1 or B_2 responses, irrespective of the reinforcer distribution. Inherent bias is often attributed to undetected asymmetries in the apparatus (e.g., one key requires less force to peck than the other) or the subject (e.g., color or side preferences) (Baum, 1974).

The most widely-used behavioral descriptor of signal-detection performance is Davison and Tustin's (1978) GML-based model. They proposed that when two stimuli (S_1 and S_2) are indistinguishable, the distribution of responses across the two response alternatives (B_1/B_2) should depend on the relative distribution of reinforcers for the two alternatives (R_1/R_2) in the manner of the GML (Equation 1). However, once the stimuli become more distinguishable, behavior also becomes biased towards making correct (B_{11} and B_{22}) responses. Choice in detection tasks is described on S_1 trials by

$$\log\left(\frac{B_{11}}{B_{12}}\right) = a\log\left(\frac{R_{11}}{R_{22}}\right) + \log c + \log d, \quad (2)$$

and on S_2 trials by

$$\log\left(\frac{B_{21}}{B_{22}}\right) = a\log\left(\frac{R_{11}}{R_{22}}\right) + \log c - \log d, \quad (3)$$

where B_{11}, B_{12}, B_{21}, and B_{22}, a, and log c are as above, and R_{11} and R_{22} are the numbers of reinforcers obtained for correct B_{11} and B_{22} responses respectively. The parameter log d measures discriminability between the two stimuli, S_1 and S_2. When log $d = 0$, the stimuli are not discriminated and Equations 2 and 3 reduce to the GML. As discriminability (log d) increases, subjects make more B_1 responses following S_1 (B_{11}) and more B_2 responses following S_2 (B_{22}); hence, log d is additive in Equation 2 and subtractive in Equation 3.

Algebraic subtraction and addition of Equations 2 and 3 allows separate calculation of point estimates of discriminability and bias. Algebraic subtraction provides a bias-free measure of discriminability:

$$\log d = 0.5\log\left(\frac{B_{11}B_{22}}{B_{12}B_{21}}\right) \quad (4)$$

where all notation is as above. Algebraic addition of Equations 2 and 3 provides a discriminability-free measure of response bias:

$$\begin{aligned}\log b &= 0.5\log\left(\frac{B_{11}B_{21}}{B_{12}B_{22}}\right)\\ &= a\log\left(\frac{R_{11}}{R_{22}}\right) + \log c\end{aligned} \quad (5)$$

where all notation is as above. Equation 5 states that response bias (log b) incorporates both reinforcer effects and inherent bias (log c), as described by the GML.

Davison and Tustin's (1978) behavioral model of signal detection has described choice behavior well when relative reinforcer frequencies or magnitudes are varied (e.g., Boldero, Davison, & McCarthy, 1985; McCarthy & Davison, 1979). The model also predicts an independence between its parameters, for example, changes in the distribution of reinforcers (R_{11}/R_{22}) should not produce systematic changes in discriminability (log d), and changes in discriminability should not affect sensitivity to the reinforcer distribution (a). However, there is conflicting evidence regarding whether these assumptions of independence are met (see Alsop & Porritt, 2006; Johnstone & Alsop, 1999). Despite these limitations, the model is still widely used for detection and matching-to-sample data analyses.

Davison and Tustin's (1978) model and subsequent research (see Davison & McCarthy, 1988, for a summary) has focused almost exclusively on the effects of varied reinforcer contingencies. In contrast, the effects of punishers for errors have received relatively little attention (but see Galanter & Holman, 1967; Hume & Irwin, 1974; Wright & Nevin, 1974). Hume and Irwin investigated the effects of varied punisher (time-outs) contingencies using a detection procedure with rats but found little effect of varied relative time-out durations on response bias. Galanter and Holman varied both relative monetary gains and losses and found participants were biased towards responding on the alternative associated with the greater monetary gain and the smaller monetary loss. Finally, Wright and Nevin varied the intensity of shock punishment on one alternative then increased the frequency of reinforcement for that alternative and found changes in the location (but not the slope) of the bias function. The lack of punishment research with detection procedures is of concern because, like reinforcers, punishers are common in many real-world detection tasks (e.g., toxic pollen might kill the bee). Ideally, any model of detection should describe both the effects of reinforcement for correct responses and the effects of punishment for errors.

To incorporate punishment into a detection model, it seems obvious to examine how the effects of punishers and reinforcers are modeled in standard concurrent schedules. There are two main competing models—an additive model (e.g., Deluty, 1976) and a subtractive model (e.g., de Villiers, 1980; Farley & Fantino, 1978). The additive model proposes that the effects of punishment on one response alternative add to the effects of reinforcement on the other alternative, while the subtractive model proposes that the effects of punishment directly subtract from reinforcer effects on the same alternative. Few studies have investigated the predictions of these models, but there appears to be more empirical support for the subtractive model (Critchfield, Paletz, MacAleese, & Newland, 2003; de Villiers, 1980; Farley, 1980; Farley & Fantino, 1978) than the additive model (Deluty, 1976). Both models are readily incorporated into Davison and Tustin's (1978) GML-based model of signal detection (Equations 2 and 3). When correct responses are intermittently reinforced and errors are intermittently punished, the additive punishment version (e.g., Deluty, 1976) of Davison and Tustin's model is, following S_1 presentations,

$$\log\left(\frac{B_{11}}{B_{12}}\right) = a\log\left(\frac{R_{11} + qP_{12}}{R_{22} + qP_{21}}\right) + \log c + \log d, \tag{6}$$

and following S_2 presentations,

$$\log\left(\frac{B_{21}}{B_{22}}\right) = a\log\left(\frac{R_{11} + qP_{12}}{R_{22} + qP_{21}}\right) + \log c - \log d, \tag{7}$$

with response bias calculated as

$$\begin{aligned}\log b &= 0.5\log\left(\frac{B_{11}B_{21}}{B_{12}B_{22}}\right)\\ &= a\log\left(\frac{R_{11} + qP_{12}}{R_{22} + qP_{21}}\right) + \log c.\end{aligned} \tag{8}$$

Notation is as above, but now P_{12} and P_{21} are the numbers of obtained punishers for incorrect B_{12} and B_{21} responses respectively, and q is a scaling parameter used to equate the value of one punisher relative to one reinforcer (e.g., if $q = .5$, then a punisher would be half the perceived value of a reinforcer). In Equations 6 to 8, the effects of punishers obtained on one response alternative (e.g., P_{12} for incorrect B_2 responses) *add* to the effects of reinforcers obtained for the other response alternative (e.g., R_{11} for correct B_1 responses).

Likewise, a subtractive punishment version (e.g., de Villiers, 1980; Farley, 1980) of Davison and Tustin's (1978) model can be written, following S_1 presentations

$$\log\left(\frac{B_{11}}{B_{12}}\right) = a\log\left(\frac{R_{11} - qP_{21}}{R_{22} - qP_{12}}\right) + \log c + \log d, \tag{9}$$

and following S_2 presentations by

$$\log\left(\frac{B_{21}}{B_{22}}\right) = a\log\left(\frac{R_{11} - qP_{21}}{R_{22} - qP_{12}}\right) + \log c - \log d, \tag{10}$$

with response bias calculated as

$$\log b = 0.5 \log\left(\frac{B_{11}B_{21}}{B_{12}B_{22}}\right) = a \log\left(\frac{R_{11} - qP_{21}}{R_{22} - qP_{12}}\right) + \log c, \quad (11)$$

where all notation is as above. In Equations 9, 10, and 11, the effects of punishers obtained on one response alternative (e.g., P_{21} for incorrect B_1 responses) *subtract* from the effects of reinforcers obtained on the same response alternative (e.g., R_{11} for correct B_1 responses). Note that Equations 9, 10, and 11 are undefined if qP_{21} is greater that R_{11} or qP_{12} is greater than R_{22}.

Figure 2 illustrates bias predictions made by the additive (Equation 8) and subtractive (Equation 11) punishment versions of Davison and Tustin's (1978) model under two different reinforcer and punisher arrangements. In the first arrangement (Figure 2, top), relative punisher frequency was varied from 1:11 to 11:1 (variable interval [VI] 60 s:VI 5.5 s to VI 5.5 s:VI 60 s) with a constant and equal (VI 3 s:VI 3 s) background rate of reinforcement. Figure 2 (top) shows that the additive (dotted line) and subtractive (dashed line) models predict systematic biases away from the more punished alternative (i.e., negatively sloping functions) with the subtractive model predicting slightly more extreme response biases than the additive model.

Figure 2 (bottom) shows the predictions of both models when relative reinforcer frequency was varied (7:1 to 1:7) with a constant and equal (1:1) background rate of punishment. A reinforcer-only baseline, where the relative reinforcer frequency was varied (7:1 to 1:7) without any punishment for errors, is also shown for comparison (solid line). When subjects received a constant and equal rate of punishers for errors, the additive and subtractive models make different predictions. The additive model (dotted line) predicts a shallower function than the reinforcer-only conditions; that is, it predicts a reduced preference for the more reinforced alternative. The subtractive model (dashed line) predicts a steeper (and nonlinear) function than the reinforcer-only conditions; that is, it predicts an increased preference for the more reinforced alternative.

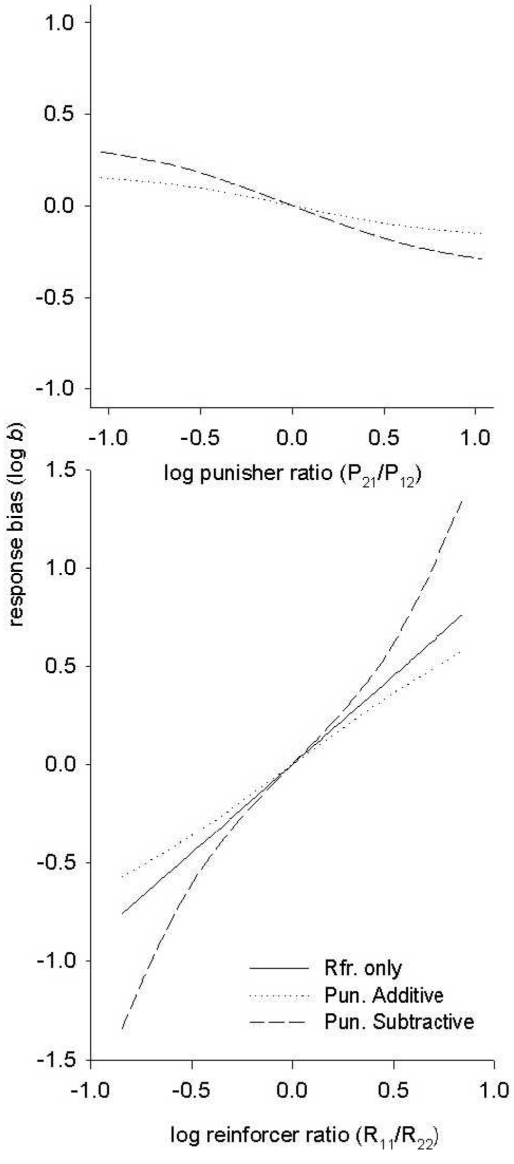

Fig. 2. Predictions made by punishment versions of Davison and Tustin's (1978) GML-based model of signal detection. The effects of varied punisher ratio (top) and reinforcer ratio (bottom) on response bias (log *b*) are plotted for additive model predictions (dotted lines), and subtractive model predictions (dashed lines), when $a = .9$, $\log c = 0$, and $q = 1$. Figure 2 (bottom) also plots the predicted changes in response bias when the relative reinforcer ratio is varied without punishment for errors (solid line).

The present experiments examined the effects of punishment for errors in detection procedures using human participants. Historically, the most commonly used punisher for nonhuman subjects in behavioral experiments was electric shock (Baron, 1991). Due to ethical constraints associated with using human participants however, response cost was chosen as the punisher type for the present experiments. Response cost has been an effective aversive stimulus in both basic (Crosbie, 1998) and applied (Lerman & Vorndran, 2002) settings, and is defined as the contingent removal of conditioned reinforcers, such as points (Weiner, 1962, 1963) or money (Critchfield, et al., 2003). In the present experiments, reinforcers were point gains and punishers were point losses. These points were exchangeable for reduced session time (i.e., point losses resulted in increased session time) and Experiment 1 investigated whether these were effective reinforcers and punishers for human participants. Experiments 2 and 3 examined which of the two competing models (additive or subtractive) was a better descriptor of choice in detection procedures.

EXPERIMENT 1

Experiment 1 used a perceptual discrimination task where participants judged whether stimulus arrays contained more blue or yellow objects (e.g., Johnstone & Alsop, 1996, 2000). Two groups of participants were used—Group A examined the efficacy of point-gain reinforcers while Group B examined the effects of point-loss punishers. For Group A, the ratio of reinforcers for correct responses (R_{11}:R_{22}) varied across four conditions (5:1, 2:1, 1:2, and 1:5) with no punishers for errors. It was predicted that Group A participants would be systematically biased towards responding to the more reinforced alternative, consistent with the GML (Equation 5) and previous human (e.g., Alsop, Rowley, & Fon, 1995; Johnstone & Alsop, 1996) and nonhuman (e.g., McCarthy & Davison, 1979) detection research. For Group B, the ratio of punishers for errors (P_{21}:P_{12}) varied across four conditions (5:1, 2:1, 1:2, and 1:5) against a background of a 1:1 reinforcer ratio for correct responses. It was predicted that participants in Group B would be systematically biased away from responding to the more punished alternative (Equations 8 and 11, and Figure 2, top).

Method

Participants

Undergraduate students at the University of Otago participated as part of an optional piece of assessment. In Group A, there were 1 male and 5 females aged between 18 to 19 years (*M* = 18.3 years). In Group B, there were 3 males and 3 females aged between 18 to 21 years (*M* = 19.0 years).

Apparatus

The experiment was conducted in a room approximately 2.3 m × 3.0 m. A computer ran the tasks and recorded the participants' responses using a program written in Microsoft VisualBasic™ 6.0. Stimuli and instructions were presented on a standard 38 cm (15″) color monitor. Stimuli were 10 × 10 arrays (129 mm wide × 138 mm high) in the center of a white screen with each position of the array occupied by either a blue ''greeblie'' or yellow ''greeblie'' (i.e., alien cartoon characters). Each greeblie was approximately 10 mm wide by 12 mm high against a white background. Stimuli classified as ''more blue'' consisted of at least 52 array positions filled randomly with blue greeblies and no more than 48 array positions filled with yellow greeblies. Stimuli classified as ''more yellow'' had at least 52 yellow greeblies and no more than 48 blue greeblies. As described below (Procedure), the final proportions of blue and yellow greeblies depended on each participant's performance.

Participants responded by clicking the computer mouse over one of two response ''boxes'' presented on the computer screen 1.5 cm under each stimulus array and 7 cm apart from one another. Each response box was 4 cm wide by 1.5 cm high. The left and right boxes were colored and labeled ''blue'' and ''yellow'' respectively. An arrow-shaped cursor indicated the virtual position of the computer mouse on the screen. Figure 3 shows an example of a stimulus array with the responses boxes presented below.

Procedure

All participants attended four experimental sessions (one condition per session), no less than 24 hours apart and no more than one week apart. The order of conditions was partially counterbalanced across participants (Table 1). Participants read an information sheet which briefly described the experiment and signed an informed consent form before the start of the first session. They were then

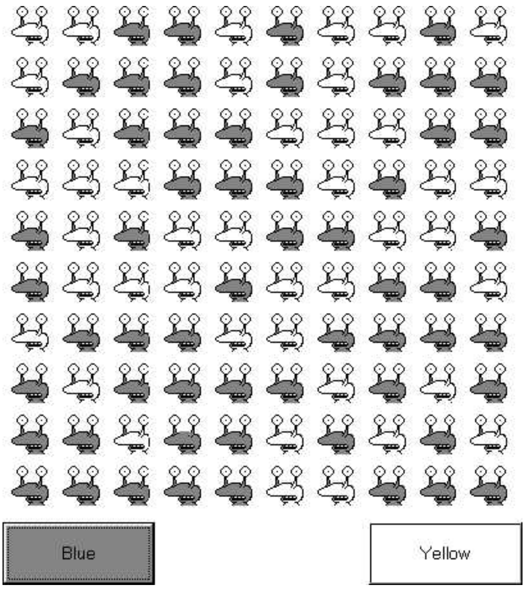

Fig. 3. An illustrative example of a ''more blue'' stimulus array with the response buttons presented during each trial in Experiment 1.

seated with their heads approximately half a meter away from the computer screen.

Group A. The following set of instructions was presented on the computer screen at the start of each session. Participants advanced screens using the computer mouse to click the ''next screen'' button located at the bottom left corner of the screen.

> Screen 1: *"Hi, this is a simple computer game. You will see some patterns of blue greeblies and yellow greeblies. You must decide if there are more blue ones or yellow ones, and then press the blue or yellow button. Here is an example of a pattern."*
> Screen 2: *"If there are more blue greeblies, press the blue button."* An example array showing more blue greeblies was presented.
> Screen 3: *"If there are more yellow greeblies, press the yellow button."* An example array showing more yellow greeblies was presented.
> Screen 4: *"Sometimes when you are correct you will gain a point. Sometimes nothing happens, you might be correct or wrong. When you get 70 points, the session will end and you can go!"*
> Screen 5: *"As you go, a red bar (like that on the right) will show you how close you are to finishing the experiment. When the red bar gets to the top, you can go!"* A vertical thermometer bar was presented on the right side of Screen 5.
> Screen 6: *"Any questions? If not, you are ready to start the session."* The ''Begin Experiment'' button appeared.

Each trial began with a 15 mm × 15 mm animated picture of a juggler (warning stimulus) in the middle of the screen for 1 s. A stimulus array (containing either more blue or yellow greeblies) and the two response boxes then appeared. The array remained on screen until the participant clicked on a response box, or for a maximum of 3 s. If the participant had not responded after the 3-s stimulus presentation, the array disappeared and the response boxes remained on the screen until the participant clicked one of them. The response boxes then disappeared.

Following each response, there were two possible consequences. If a reinforcer had not been scheduled for that response, the screen went blank for 1 s (i.e., no consequence), followed by a 1-s intertrial interval (ITI). A ''next trial'' button then appeared in the center of the screen. A click on the button started the next trial.

If the participant made a correct response (B_{11} or B_{22}) and a reinforcer was scheduled for that response, the statement: ''*Correct! You are one point closer to finishing the session*'', appeared on the center of the screen for 2 s. This was accompanied by a 1-s ''ta da!'' sound and a thermometer bar appeared on the right side of the screen. The bar was divided into 70 blank spaces (the number of points required to exit the session). Each time the participant obtained a point, one space of the bar was filled in red, indicating that the bar had gone up. A 1-s ITI then followed, the ''next trial'' button appeared on the screen, and the participant clicked the button to start the next trial.

The stimulus presentation probability (SPP) was set at .5 throughout the experiment; that is, on any trial, the participants were equally likely to be presented with a stimulus array containing ''more blue'' or ''more yellow'' greeblies. The difficulty level of the discrimination was titrated for each participant to make accuracy levels across participants more equal. Each session began with 56 greeblies of one color and 44 greeblies of the other color (56:44). After the 20^{th} trial, the computer program analyzed performance over the last 16 trials. If the percentage of correct responses was greater than 90% across the 16 trials, the proportions were made more equal by a subtraction factor of 2 (e.g., a 56:44 distribution was reduced to 54:46). If the percentage of correct responses was between 70% and 90% for the previous 16

Table 1

The numbers of B_{11}, B_{12}, B_{21}, and B_{22} responses, R_{11} and R_{22} reinforcers, P_{21} and P_{12} punishers, and estimates of discriminability (log *d*) and response bias (log *b*) calculated across the last 120 trials for each participant in each condition in Group A (varied reinforcer ratios) and Group B (varied punisher ratios) of Experiment 1. The more reinforced (Group A) or punished (Group B) alternative is presented in bold and underlined for each condition.

Part.	Cond.	Order	B_{11}	B_{12}	B_{21}	B_{22}	R_{11}	R_{22}	P_{21}	P_{12}	log *d*	log *b*
						GROUP A						
DN	**5**:1	1	54	7	22	37	27	5	0	0	0.56	0.33
	2:1	3	52	9	18	41	24	12	0	0	0.56	0.20
	1:**2**	4	40	21	6	53	11	21	0	0	0.61	−0.33
	1:**5**	2	25	34	11	50	4	27	0	0	0.26	−0.40
EW	**5**:1	2	50	9	22	39	28	7	0	0	0.50	0.25
	2:1	4	44	16	24	36	22	8	0	0	0.31	0.13
	1:**2**	3	28	30	19	43	11	18	0	0	0.16	−0.19
	1:**5**	1	32	28	10	50	5	24	0	0	0.38	−0.32
GJS	**5**:1	3	46	15	36	23	23	4	0	0	0.15	0.34
	2:1	1	50	10	24	36	23	10	0	0	0.44	0.26
	1:**2**	2	34	26	22	38	9	20	0	0	0.18	−0.06
	1:**5**	4	30	30	11	49	5	25	0	0	0.32	−0.32
KP	**5**:1	4	45	17	19	39	22	6	0	0	0.37	0.06
	2:1	2	41	20	18	41	23	11	0	0	0.33	−0.02
	1:**2**	1	35	23	13	49	11	21	0	0	0.38	−0.20
	1:**5**	3	42	18	28	32	4	19	0	0	0.21	0.15
SLJ	**5**:1	1	38	22	34	26	20	5	0	0	0.06	0.18
	2:1	3	48	12	17	43	24	13	0	0	0.50	0.10
	1:**2**	2	24	39	9	48	8	17	0	0	0.26	−0.47
	1:**5**	4	40	21	12	47	5	28	0	0	0.44	−0.16
SC	**5**:1	3	44	15	24	37	24	6	0	0	0.33	0.14
	2:1	2	48	13	15	44	18	11	0	0	0.52	0.05
	1:**2**	4	31	30	18	41	8	17	0	0	0.19	−0.17
	1:**5**	1	30	30	10	50	6	25	0	0	0.35	−0.35
						GROUP B						
DLG	**5**:1	4	42	19	13	46	16	11	9	2	0.45	−0.10
	2:1	2	25	35	5	55	17	13	4	1	0.45	−0.59
	1:**2**	1	52	8	10	50	19	20	2	4	0.76	0.06
	1:**5**	3	51	9	17	43	17	15	2	7	0.58	0.18
HLB	**5**:1	3	39	20	14	47	15	15	10	2	0.41	−0.12
	2:1	1	36	24	10	50	14	12	5	3	0.44	−0.26
	1:**2**	4	32	31	16	41	14	12	5	11	0.21	−0.20
	1:**5**	2	52	8	20	40	16	15	0	6	0.56	0.26
JA	**5**:1	1	50	9	13	48	19	21	8	1	0.66	0.09
	2:1	3	41	19	11	49	18	18	9	4	0.49	−0.16
	1:**2**	2	41	19	9	51	17	18	4	9	0.54	−0.21
	1:**5**	4	48	12	15	45	20	17	2	7	0.54	0.06
JH	**5**:1	3	45	15	5	55	19	16	4	0	0.76	−0.28
	2:1	1	41	19	18	42	16	14	9	4	0.35	−0.02
	1:**2**	2	44	14	23	39	15	13	5	10	0.36	0.13
	1:**5**	4	55	6	23	36	16	13	0	3	0.58	0.38
KMC	**5**:1	2	37	22	20	41	16	12	10	2	0.27	−0.04
	2:1	4	36	25	22	37	12	13	9	3	0.19	−0.03
	1:**2**	3	40	19	13	48	15	17	3	8	0.45	−0.12
	1:**5**	1	42	18	22	38	14	16	2	12	0.30	0.07
PN	**5**:1	1	33	28	7	52	13	15	6	0	0.47	−0.40
	2:1	3	31	28	12	49	13	15	7	5	0.33	−0.28
	1:**2**	4	40	19	12	49	12	16	3	6	0.47	−0.14
	1:**5**	2	38	23	12	47	16	15	2	15	0.41	−0.19

trials, the proportions were made more equal by a subtraction factor of 1 (e.g., 56:44 became 55:45). If the percentage of correct responses was between 60% and 70%, the proportions remained the same. If the participant received less than 60% correct, then the proportions were made more different by a factor of 1 (e.g., 56:44 became 57:43). The program then continued to analyze the previous 16 trials after every block of 10 trials, and titrated difficulty ratios accordingly. Following the 60^{th} trial, the difficulty level (proportion of blue and yellow greeblies) remained constant throughout the remainder of the session. The most difficult ratio was limited to 52:48, but there was no limit set on the least difficult ratio.

The relative distribution of reinforcers across the two response alternatives was allocated using interdependent scheduling (Stubbs & Pliskoff, 1969), also known as a *controlled* procedure in behavioral signal-detection research (e.g., McCarthy & Davison, 1984), to ensure that arranged and obtained relative distributions were similar. The computer randomly scheduled the next reinforced correct response (''more blue'' or ''more yellow'') according to the arranged reinforcer frequency ratio (R_{11}:R_{22}). This varied across the four conditions (5:1, 2:1, 1:2, and 1:5). For example, if the participant was in the 5:1 condition, they were five times more likely to receive reinforcers for correctly responding on the left response box (''more blue'') following a ''more blue'' stimulus presentation (B_{11}) than for correctly responding on the right response box (''more yellow'') following a ''more yellow'' stimulus presentation (B_{22}). The overall scheduled rate of reinforcement across the two response alternatives was based on a VI 10-s schedule. The VI schedule timer ran through each trial (i.e., through the warning stimulus presentation, array presentation, the time the participant took to respond, and the consequence), and only paused at the end of each trial (from the presentation of the ''next trial'' button to when the participant clicked on the button). Each session ended when the participant reached a total of 70 points, or when the participant reached the 400^{th} trial, whichever came first.

Group B. Group B participants performed a similar task to those in Group A. However, Group B participants also received occasional punishers (point losses) for errors. Screen 4 was changed accordingly to:

Screen 4: *"Sometimes when you are correct you will gain a point. Sometimes nothing happens, you might be correct or wrong. Sometimes when you are wrong you will lose a point. When you get 60 points, the session will end and you can go!"*

Thus, there were three possible consequences following each response. Like Part A, participants could receive no consequence if neither a reinforcer nor punisher was scheduled for that particular response (i.e., 1-s blank screen), or a reinforcer if they made a correct response (B_{11} or B_{22}) and a reinforcer was scheduled for that response (see Group A for details). The third consequence occurred if the participant made an incorrect response (B_{12} or B_{21}) and a punisher was scheduled. The statement: *"Incorrect! You are one point further from finishing the session!"* appeared on the center of the screen for 2 s, accompanied by a 1-s ''argh!'' sound and the thermometer bar. One space of the red bar was deleted, showing that the bar had gone down. All three consequence types were followed by a 1-s ITI and the presentation of the ''next trial'' button. Although participants were informed that the session ended after 60 points, like Group A, the session actually ended when the participant had obtained 70 point-gain reinforcers (irrespective of how many point-loss punishers they had received), or when the participant reached the 400^{th} trial, whichever came first.

Like Group A, the distributions of reinforcers and punishers were allocated using interdependent scheduling. The distribution of reinforcers was held constant and equal (1:1) for Group B; that is, participants received equal numbers of reinforcers for correct B_{11} and B_{22} responses. For punishers, the computer program randomly scheduled the next incorrect response to be punished according to the arranged punisher ratio. For Group B, the punisher frequency ratio (P_{21}:P_{12}) was varied across the four conditions; these were 5:1, 2:1, 1:2, and 1:5. The overall rate of reinforcement across the two response alternatives was based on a VI 10-s schedule, while the overall rate of punishment was on a VI 20-s schedule. Both VI timers ran during each trial, and paused between the presentation of the ''next trial'' button and the participants' response to the button.

Results and Discussion

Experimental sessions lasted approximately 25 to 35 min, with an average of 277 trials completed (*SD* = 32.9). The last 120 trials from each experimental session were analyzed separately for each participant in Groups A and B of Experiment 1. For these data, the number of left button ("more blue") responses following S_1 (B_{11}) and S_2 (B_{12}) and right button ("more yellow") responses following S_1 (B_{21}) and S_2 (B_{22}) were calculated. The number of reinforcers (point gains) obtained for correct responses on each button (R_{11} and R_{22}) and the number of punishers (point losses) obtained for errors on each button (P_{21} and P_{12}) were also calculated. Measures of discriminability (log *d*, Equation 4) and response bias (log *b*, Equation 5) were calculated for each participant from each condition (Table 1).

Figure 4 (top) plots estimates of discriminability (log *d*) across the four reinforcer or punisher ratios for each participant in Groups A (left) and B (right) of Experiment 1. Estimates of discriminability did not significantly differ across the four conditions for participants in Group A, $F(3,15) = 1.244$, $p = .33$, or Group B, $F(3,15) = 1.270$, $p = .32$. This independence between discriminability and relative reinforcer (Group A) and punisher (Group B) frequency was consistent with Davison and Tustin's (1978) model. However, a mixed 4 (Condition) × 2 (Group) analysis of variance (ANOVA) found that the difference in discriminability between the two groups approached significance, $F(1,10) = 4.474$, $p = .06$; that is, mean discriminability for Group B participants ($M = .46$) was somewhat higher than mean discriminability for Group A participants ($M = .35$). It is possible this was a result of participants in Group B receiving more feedback than those in Group A. For example, Group A participants obtained 70 reinforcers (points) in an average of 271 trials; that is, about 26% of trials ended with feedback. In comparison, Group B participants obtained 70 reinforcers and an average of 24.5 punishers in an average of 282 trials; that is, about 34% of their trials ended with feedback (i.e., reinforcement or punishment). However, it is also possible that the sample of participants chosen for Group B were better at numerosity judgments than participants in Group A, irrespective of the punisher contingencies.

Figure 4 (bottom) plots estimates of response bias (log *b*) across the four reinforcer or punisher ratios for each participant in Groups A (left) and B (right) of Experiment 1[1]. For Group A, estimates of response bias differed significantly across conditions, $F(3,15) = 13.38$, $p < .001$. Individual estimates of sensitivity (i.e., slopes) calculated using least squares linear regression analyses on the response bias data for each participant found positive slopes for 5 of the 6 participants ($M = .36$), and a one-sample *t*-test performed on these slopes confirmed that they were significantly greater than zero, $t(5) = 4.355$, $p < .01$. In other words, participants in Group A were systematically biased towards responding on the alternative associated with the higher frequency of reinforcement. These results were consistent with the standard (reinforcement-only) version of Davison and Tustin's (1978) model (Equation 5). Furthermore, mean sensitivity (0.36) was comparable to those obtained in previous human detection experiments (e.g., Alsop, et al., 1995; Johnstone & Alsop, 1996).

For Group B, estimates of response bias also varied systematically across the four conditions, $F(3,15) = 4.387$, $p < .05$, and least squares linear regression analyses performed on each participant found negative slopes for 5 of the 6 participants ($M = -.20$). A one-sample *t*-test confirmed that estimates of sensitivity for Group B participants were significantly less than zero, $t(5) = 2.765$, $p < .05$; that is, participants in Group B were systematically biased away from the response alternative associated with the higher frequency of point-loss punishment. Although the mean slope (−0.20) obtained from Group B was shallower than that obtained from Group A (0.36), this is perhaps not surprising because participants in Group B also received equal rates of reinforcers (at a higher overall rate than the punishers); thus, the effect of the reinforcers should attenuate the effect of the punishers. The results from Group B were consistent with both punishment versions of Davison and Tustin's (1978) signal-detection model (Equations 6 to 11; Figure 2, top), which predict a negative relation between relative punisher frequency and response bias. Overall, Experiment 1 demonstrated that point gains for correct responses were effective reinforcers (Group A) and that point losses for errors were effective punishers (Group B) for human participants in a detection procedure.

[1] A summary of these data were presented in a short theoretical article by Lie & Alsop (2007).

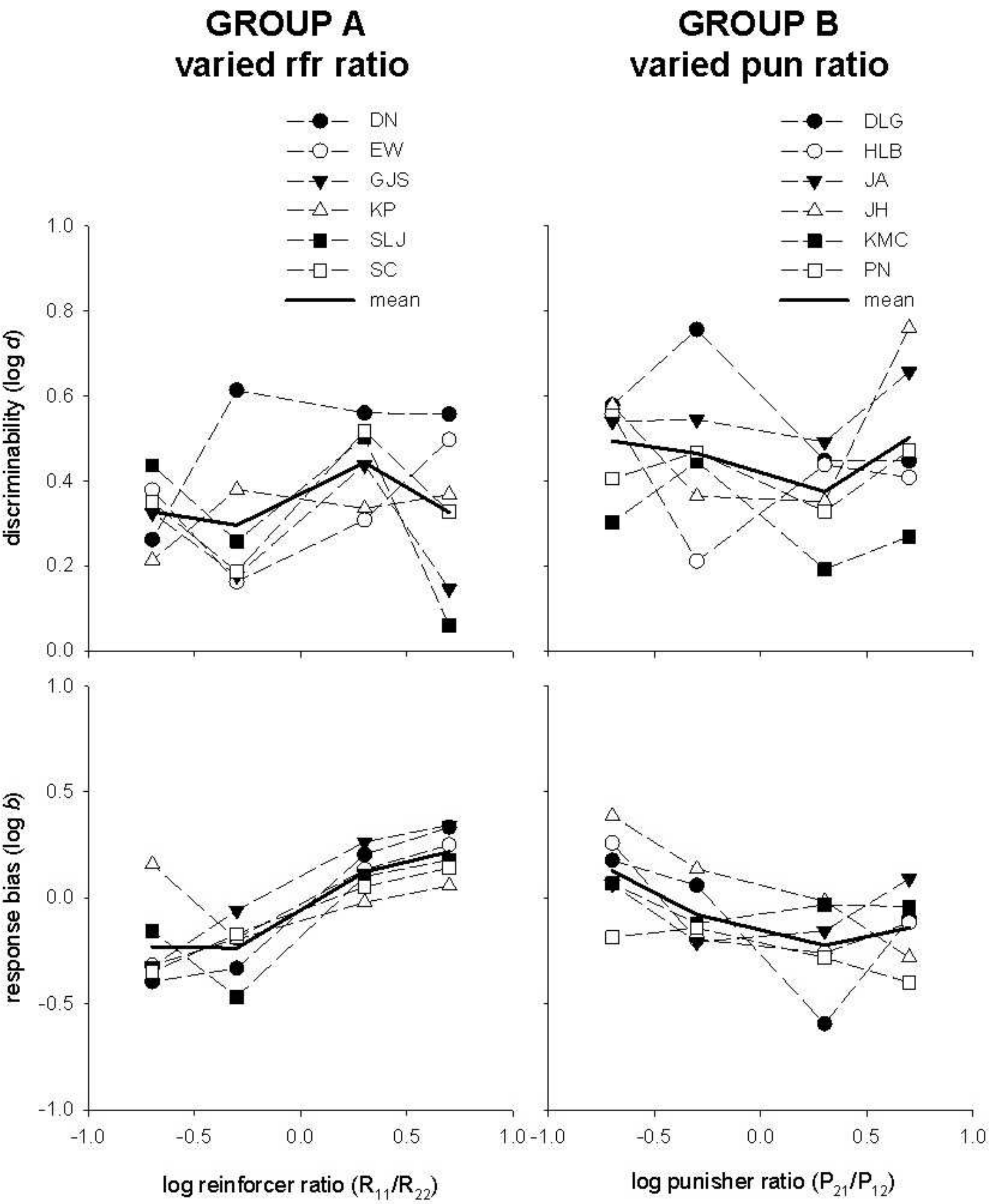

Fig. 4. Discriminability (log d – top) and response bias (log b – bottom) are plotted over changes in relative reinforcer frequency (log R_{11}/R_{22}) for Group A (left) and relative punisher frequency (log P_{21}/P_{12}) for Group B (right) of Experiment 1. Individual participant data and the overall means are given.

EXPERIMENT 2

Experiment 1 established that point gains and losses were effective reinforcers and punishers respectively, and that the punishers had similar but opposite effects to reinforcers on human signal-detection performance. Experiments 2 and 3 examined whether additive (e.g., Deluty, 1976) or subtractive (e.g., de Villiers, 1980; Farley, 1980) models of punishment better model the effects of punishment in signal detection. These two competing models make different predictions when relative reinforcer frequency is varied and a constant and equal rate of punishment is superimposed on both response alternatives. When relative reinforcer frequency is varied in the absence of punishment, behavior can be described by Davison and Tustin's (1978) GML-based model of signal detection (Equation 5, and Figure 2 bottom, solid line). However, when a constant and equal rate of punishment is also included, the additive punishment version of Davison and Tustin's model (Equation 8) predicts a reduced preference for the more reinforced response alternative (Figure 2 bottom, dotted line), while the subtractive punishment version of Davison and Tustin's model (Equation 11) predicts an increased preference for the more reinforced alternative (Figure 2 bottom, dashed line).

Although no published studies have tested the predictions of the two competing models using signal-detection procedures, some research has tested the two models using standard concurrent-schedule procedures (Critchfield, et al., 2003; de Villiers, 1980; Deluty, 1976; Farley, 1980). One approach involves arranging a constant and unequal distribution of reinforcers across two alternatives (reinforcer-only [R-only] condition) then superimposing a constant and equal distribution of punishers (reinforcer + punisher [R+P] condition) and measuring preference under both condition types. Using this arrangement, the subtractive model predicts increased preference for the richer (i.e., more reinforced) alternative with the inclusion of punishment (i.e., greater preference in R+P conditions than R-only conditions), while an additive model predicts decreased preference for the richer alternative (i.e., greater preference in R-only conditions than R+P conditions).

A number of researchers have taken this approach. Using pigeons as subjects and electric shock punishers, both Farley (1980) and de Villiers (1980) found increased preference for the rich alternative in conditions where electric shock was superimposed across both alternatives (R+P conditions) when compared to a baseline condition where unequal concurrent schedules of reinforcement were presented without electric shock (R-only condition). Critchfield et al. (2003) also found an increase in preference for the rich alternative when an equal distribution of point-loss punishers was superimposed on unequal concurrent schedules of point-gain reinforcement using human participants. Thus, these studies unanimously supported a subtractive model of punishment over an additive model for concurrent-schedule performance.

Experiment 2 used the same perceptual discrimination task as Experiment 1 and arranged two conditions: an R-only condition where the reinforcer ratio was held constant and unequal at either 1:5 or 5:1 with no punishers for errors, and an R+P condition where the same reinforcer ratio was arranged but with a 1:1 punisher ratio superimposed. A comparison of estimates of response bias between R-only and R+P conditions should indicate whether an additive or subtractive punishment model better describes human signal-detection performance.

Method

Participants

Undergraduate students at Victoria University of Wellington participated as part of an optional piece of assessment. There were 8 males and 8 females aged between 18 and 35 years ($M = 20.1$ years).

Apparatus

The apparatus and stimuli were similar to those used in Experiment 1. However, the experiment was conducted in a room approximately 5 m × 5 m and the task was presented on a 43 cm (17″) LCD screen. Half the participants were presented with 10 × 10 arrays of blue and yellow greeblies (the same as Experiment 1) while the other half were presented with 10 × 10 arrays consisting of red and (darker) blue greeblies. (Anecdotal evidence from the first experiment suggested that the yellow greeblies were more salient than the blue greeblies). Due to changes in screen size and resolution for Experiment 2, the 10 × 10 arrays measured approximately 118 mm wide by 119 mm high, with each greeblie measuring approximately 8.5 mm wide by 9.0 mm high (i.e., slightly smaller than in Experiment 1). All other aspects of the apparatus and stimuli were identical to Experiment 1.

Procedure

The general procedure for Experiment 2 was similar to Experiment 1. However, there were only four condition types in Experiment 2: two R-only conditions (5:1R and 1:5R) and two R+P conditions (5:1P and 1:5P). The R-only conditions were identical to the 5:1 and 1:5 conditions for Group A of Experiment 1; that is, correct responses were occasionally reinforced and there were no punishers for errors. The reinforcer ratio was held constant at 5:1 (i.e., 5:1R condition) or 1:5 (i.e., 1:5R condition) throughout the session using interdependent scheduling and the rate of reinforcement was based on a VI 10-s schedule.

The R+P conditions were similar to Group B of Experiment 1; that is, correct responses were occasionally reinforced while errors were occasionally punished. For Experiment 2 however, the reinforcer ratio was held constant and unequal at 5:1 or 1:5 throughout the session, with a constant and equal (1:1) rate of point-loss punishers superimposed (5:1P and 1:5P conditions respectively). Like Group B of Experiment 1, the rate of reinforcement was based on a VI 10-s schedule and the rate of punishment was based on a VI 20-s schedule. For all conditions, SPP was set at .5, a titration procedure was used (see Experiment 1), and each session ended after the participant had obtained 70 points or reached 400 trials, whichever came first.

Each participant received three experimental sessions but was only presented with two conditions. Participants received the two conditions in one of two orders. For Order 1, an R-only condition was presented first, followed by an R+P condition, then the same R-only condition again (i.e., an ABA design). For Order 2, an R+P condition was presented first, followed by an R-only condition, then the R+P condition again (i.e., a BAB design). Participants were presented with the same reinforcer ratio (i.e., 5:1 or 1:5) and the same stimulus type (blue–yellow or blue–red) across all three sessions, and this was counterbalanced across all participants (Table 2).

Results and Discussion

Experimental sessions lasted approximately 30 to 40 min, with an average of 338 trials completed ($SD = 41.2$). The last 120 trials from each experimental session were analyzed for each participant in the same manner as Experiment 1. However, log *b* was calculated for all conditions with the rich alternative in the numerator (i.e., positive log *b* values reflected preference for the rich alternative). These data are presented in Table 2.

Figure 5 (top) plots estimates of discriminability (log *d*) for each participant who received Order 1 (left) or Order 2 (right) across the three sessions in Experiment 2. Like Experiment 1, estimates of discriminability did not differ significantly across the three sessions for participants who sat Order 1, $F(2,12) = .752$, $p = .49$, or Order 2, $F(2,14) = 2.351$, $p = .13$, although the means (Figure 5, solid lines) suggest that estimates of discriminability were slightly lower for R-only conditions when compared to R+P conditions, consistent with Experiment 1. A 3 (Session) $\times$ 2 (Order) ANOVA found that mean discriminability differed significantly between the two condition orders (Order 1: $M = 0.73$; Order 2: $M = 0.99$), $F(1,13) = 12.46$, $p < .01$, indicating that those who received two R+P conditions (Order 2) responded more accurately than those who only received one R+P condition (Order 1). Like Experiment 1, this could be the result of the increased feedback received in R+P conditions, or due to between-group differences.

A cursory examination of Figures 4 (Experiment 1) and 5 (Experiment 2) finds that discriminability estimates from Experiment 2 appear greater than Experiment 1. Estimates of discriminability were averaged across all three sessions for each participant in Experiment 2, and also across the 1:5 and 5:1 conditions for each participant in Experiment 1, and a two-sample *t*-test found a significant difference between Experiment 1 ($M = .42$) and Experiment 2 ($M = .86$), $t(26) = 6.756$, $p < .001$. This is not surprising, however, due to the changes in characteristics (i.e., different participant pools, changes in computer screen and stimulus array sizes, and in some cases, changes in stimulus array colors) between the two experiments.

Figure 5 (bottom) plots estimates of response bias (log *b*) for each participant who received Order 1 (left) or Order 2 (right) across the three sessions in Experiment 2. A cursory examination of the means for Order 1

Table 2

The numbers of B_{11}, B_{12}, B_{21}, and B_{22} responses, R_{11} and R_{22} reinforcers, P_{21} and P_{12} punishers, and estimates of discriminability (log *d*) and response bias (log *b*) calculated across the last 120 trials for each participant in each condition of Experiment 2.

Part.	Cond.	Order	B_{11}	B_{12}	B_{21}	B_{22}	R_{11}	R_{22}	P_{21}	P_{12}	log *d*	log *b*
						ORDER 1						
AIS	1:5R	1	42	18	19	41	19	5	0	0	0.70	0.03
	1:5P	2	54	6	34	26	25	4	5	4	0.84	1.07
	1:5R	3	48	11	33	28	22	5	0	0	0.57	0.71
AR	1:5R	1	44	17	20	39	24	6	0	0	0.70	0.12
	1:5P	2	53	7	24	36	25	5	3	5	1.06	0.70
	1:5R	3	50	11	27	32	25	6	0	0	0.73	0.58
JM	1:5R	1	52	10	28	32	18	6	0	0	0.77	0.66
	1:5P	2	51	9	31	29	25	4	2	5	0.72	0.78
	1:5R	3	51	10	31	28	19	4	0	0	0.66	0.75
MB	5:1R	1	32	28	14	46	4	26	0	0	0.57	0.46
	5:1P	2	29	31	4	56	6	22	2	4	1.12	1.18
	5:1R	3	-	-	-	-	-	-	-	-	-	-
SP	5:1R	1	50	10	18	42	4	19	0	0	1.07	−0.33
	5:1P	2	51	8	17	44	5	22	2	4	1.22	−0.39
	5:1R	3	31	29	11	49	3	21	0	0	0.68	0.62
TK	5:1R	1	34	26	19	41	4	22	0	0	0.45	0.22
	5:1P	2	34	24	11	51	5	26	7	4	0.82	0.51
	5:1R	3	33	27	20	40	5	18	0	0	0.39	0.21
YH	1:5R	1	42	18	27	33	21	5	0	0	0.46	0.28
	1:5P	2	55	7	29	29	26	5	3	6	0.90	0.90
	1:5R	3	49	11	30	30	29	5	0	0	0.65	0.65
YWO	5:1R	1	41	18	24	37	4	21	0	0	0.55	−0.17
	5:1P	2	12	48	5	55	3	18	5	3	0.44	1.64
	5:1R	3	37	23	7	53	4	19	0	0	1.09	0.67
						ORDER 2						
AC	5:1P	1	50	10	25	35	4	20	5	5	0.85	−0.55
	5:1R	2	45	15	19	41	3	22	0	0	0.81	−0.14
	5:1P	3	45	15	3	57	6	27	3	1	1.76	0.80
AS	1:5P	1	56	4	34	26	18	5	6	3	1.03	1.26
	1:5R	2	49	11	32	28	19	4	0	0	0.59	0.71
	1:5P	3	54	6	33	27	19	4	3	4	0.87	1.04
BD	1:5P	1	56	5	12	47	23	5	2	5	1.64	0.46
	1:5R	2	56	3	40	21	20	4	0	0	0.99	1.55
	1:5P	3	57	3	42	18	18	3	5	2	0.91	1.65
CL	1:5P	1	40	20	9	51	22	4	4	5	1.05	−0.45
	1:5R	2	43	16	24	37	20	4	0	0	0.62	0.24
	1:5P	3	52	8	34	26	23	4	4	4	0.70	0.93
LC	1:5P	1	57	3	31	29	20	4	3	2	1.25	1.31
	1:5R	2	50	9	31	30	20	5	0	0	0.73	0.76
	1:5P	3	58	2	23	37	21	5	0	2	1.67	1.26
RC	5:1P	1	35	26	9	50	5	22	6	4	0.87	0.62
	5:1R	2	40	21	6	53	6	23	0	0	1.23	0.67
	5:1P	3	28	32	3	57	7	23	3	2	1.22	1.34
RS	5:1P	1	49	11	24	36	6	24	5	4	0.82	−0.47
	5:1R	2	33	27	8	52	6	29	0	0	0.90	0.73
	5:1P	3	36	24	9	51	6	25	5	8	0.93	0.58
TS	5:1P	1	32	28	7	53	4	27	4	7	0.94	0.82
	5:1R	2	20	39	7	54	4	25	0	0	0.60	1.18
	5:1P	3	17	43	3	57	4	21	3	1	0.88	1.68

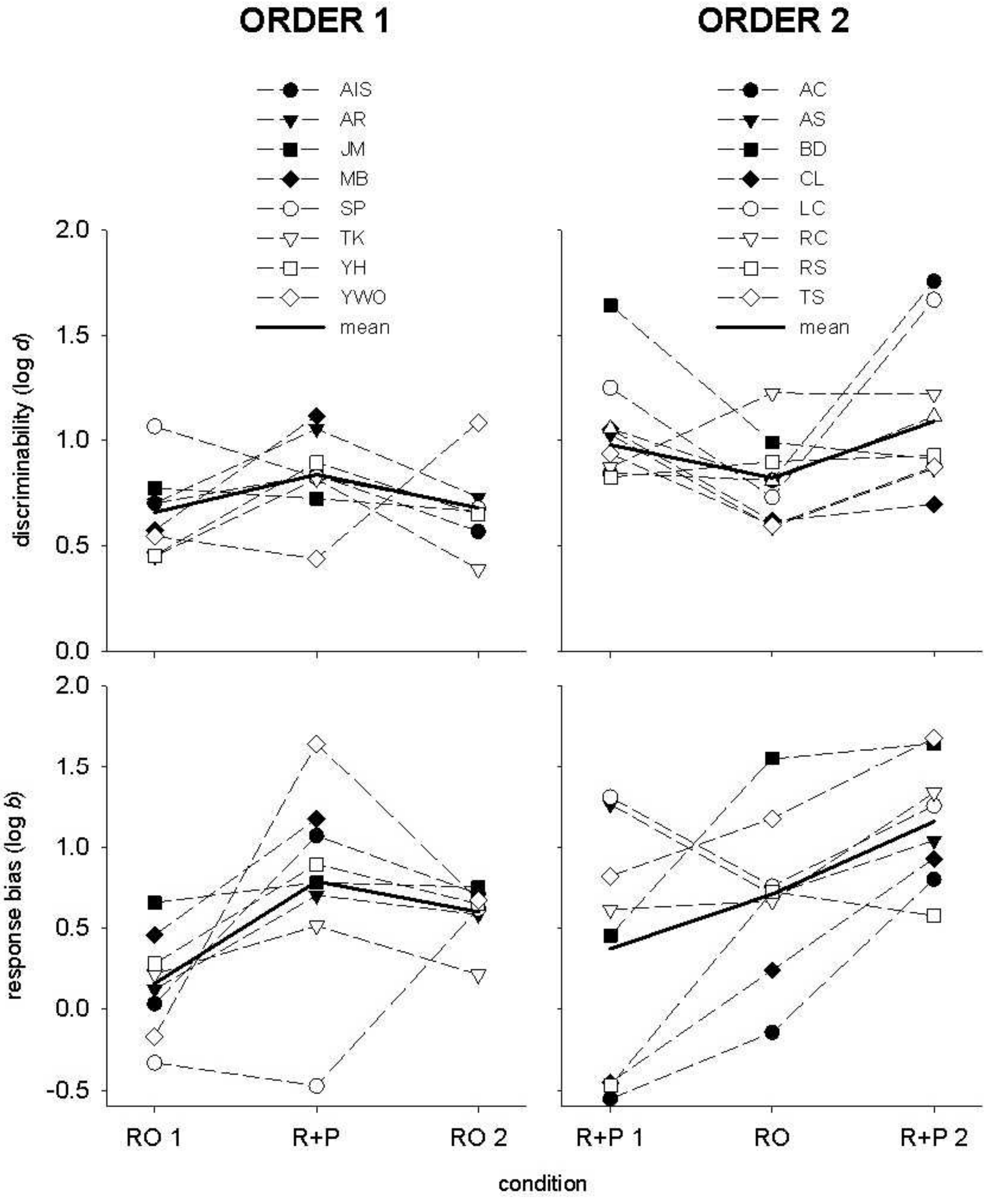

Fig. 5. Discriminability (log d – top) and response bias (log b – bottom) are plotted over the three sessions for Order 1 (R-only, R+P, R-only – left) and Order 2 (R+P, R-only, R+P – right) of Experiment 2. Individual participant data and the overall means are given.

(Figure 5, bottom left—solid lines) shows an increase in response bias from the first session (R-only condition, log $b = 0.15$) to the second session (R+P condition, log $b = 0.79$), with a slight decrease on the third session (R-only condition, log $b = 0.60$). This pattern was fairly consistent across 6 of the 8 participants[2] and a Friedman test found a significant difference in

[2] Participant MB (Figure 5 left, filled diamonds) completed all three sessions but data from the final session was lost due to a computer error. However, the increase in MB's response bias from the first to second session was also consistent with the mean findings.

response bias across the three sessions, $\chi^2 = 7.143$, $df = 2$, $p < .05$. However, paired sample t-tests only found a significant increase from R-only to R+P (Sessions 1 to 2), $t(7) = 2.960$, $p < .05$. For participants who received Order 2 (Figure 5, bottom right), there was an increase in mean estimates of log b across the three sessions (log $b = 0.37, 0.71, 1.16$), with 6 out of 8 participants showing an increase from Session 1 (R+P) to Session 2 (R-only), and 6 participants showing an increase from Session 2 (R-only) to Session 3 (R+P). While the difference across the sessions approached significance using a Friedman test, $\chi^2 = 5.250$, $df = 2$, $p = .07$, paired-sample t-tests only found a significant increase in response bias from R-only to R+P (Sessions 2 to 3), $t(7) = 3.634$, $p < .01$.

Overall, the results from both orders found significant increases in preference (i.e., response bias) from conditions that held the reinforcer ratio constant and unequal (5:1 or 1:5) with no punishment (R-only) to conditions that superimposed a constant and equal rate (1:1) of punishment onto unequal rates of reinforcement (R+P). This is consistent with the qualitative predictions made by a subtractive punishment version of Davison and Tustin's (1978) signal-detection model. It is also consistent with the findings from the concurrent-schedules literature (Critchfield, et al., 2003; de Villiers, 1980; Farley, 1980). However, the present experiment only tested the directional predictions of the additive versus subtractive models of punishment using one unequal reinforcer ratio per participant. It is unclear whether there would be an increase in preference for the rich alternative across a number of different unequal reinforcer ratios. It is also possible that the increase in preference found in the present experiment only occurred due to repeated exposure to the 1:5 or 5:1 reinforcer ratio. In fact, the significant linear trends across the three sessions for Order 1, $F(1,7) = 14.82$, $p < .01$, and Order 2, $F(1,7) = 13.11$, $p < .01$, suggests that this might have been the case. However, Johnstone and Alsop (1996) found that increased exposure to a constant and unequal reinforcer ratio did not significantly change human response bias patterns across four sessions when they used a similar detection procedure (albeit without punishers for errors). Overall, although the present experiment found support for a subtractive model of punishment, a larger study arranging several reinforcer ratios was needed.

EXPERIMENT 3

Like the previous experiment, Experiment 3 also tested the predictions of the additive versus subtractive models of detection performance. However, Experiment 3 arranged four different unequal reinforcer ratios (5:1, 2:1, 1:2, 1:5), both without (R-only) and with (R+P) a constant and equal (1:1) rate of punishment for errors. This approach has been taken by Critchfield et al. (2003) with human participants and Farley (1980) with pigeons using concurrent-schedule procedures. Both Critchfield et al. and Farley presented their subjects with conditions which varied the relative frequency of reinforcers across the two alternatives (Critchfield, et al.: from 7:1 to 1:7; Farley: from 4:1 to 1:6) with and without a constant and equal (1:1) rate of punishment superimposed across both alternatives. When estimates of sensitivity (a, Equation 1) were compared between reinforcer-only and reinforcer + punisher conditions, both studies found increased sensitivity with the inclusion of punishment, consistent with a subtractive model of punishment. If an increase in sensitivity is found in the present experiment, this would support a subtractive punishment model of detection performance (Figure 2 bottom, dashed line), consistent with the findings from concurrent-schedule procedures that have arranged similar conditions (Critchfield, et al., 2003; Farley, 1980) and also the detection procedure used in Experiment 2.

Method

Participants

Eight university students were recruited from a job recruitment agency for students at the University of Otago. Each participant received \$80NZ after the completion of their eighth and final session. There were 3 males and 5 females aged between 19 and 24 years ($M = 21.3$ years).

Apparatus

The experiment was conducted in the same room as Experiment 1 and the task was presented on a 43 cm (17″) LCD monitor.

Table 3

The numbers of B_{11}, B_{12}, B_{21}, and B_{22} responses, R_{11} and R_{22} reinforcers, P_{21} and P_{12} punishers, and estimates of discriminability (log *d*) and response bias (log *b*) calculated across the last 120 trials for each participant in each condition of Experiment 3.

Part.	Cond.	Order	B_{11}	B_{12}	B_{21}	B_{22}	R_{11}	R_{22}	P_{21}	P_{12}	log *d*	log *b*
CB	5:1R	4	43	18	17	42	25	5	0	0	0.39	−0.01
	2:1R	2	32	28	25	35	13	6	0	0	0.10	−0.04
	1:2R	3	45	20	9	56	15	24	0	0	0.57	−0.22
	1:5R	1	34	27	18	41	4	26	0	0	0.23	−0.13
	5:1P	8	31	29	17	43	17	5	7	8	0.22	−0.19
	2:1P	6	29	31	10	50	15	8	7	7	0.34	−0.36
	1:2P	7	46	14	3	57	12	22	3	5	0.90	−0.38
	1:5P	5	28	32	5	55	5	28	3	7	0.49	−0.55
CM	5:1R	3	39	20	20	41	22	3	0	0	0.30	−0.01
	2:1R	1	45	16	28	31	18	9	0	0	0.25	0.20
	1:2R	4	50	10	19	41	8	19	0	0	0.52	0.18
	1:5R	2	32	28	17	43	4	21	0	0	0.23	−0.17
	5:1P	7	32	28	8	52	20	5	7	2	0.44	−0.38
	2:1P	5	39	21	20	40	18	9	8	6	0.28	−0.02
	1:2P	8	28	33	8	51	8	17	5	1	0.37	−0.44
	1:5P	6	32	27	14	47	5	24	6	10	0.30	−0.23
CY	5:1R	5	49	11	23	37	23	6	0	0	0.43	0.22
	2:1R	7	40	20	13	47	20	8	0	0	0.43	−0.13
	1:2R	6	44	16	15	45	11	18	0	0	0.46	−0.02
	1:5R	8	26	33	11	50	4	23	0	0	0.28	−0.38
	5:1P	1	51	9	32	28	22	4	7	8	0.35	0.41
	2:1P	3	44	17	18	41	16	9	7	6	0.39	0.03
	1:2P	2	42	18	17	43	9	17	8	8	0.39	−0.02
	1:5P	4	27	35	0	58	4	23	0	0	0.98	−1.09
DK	5:1R	7	46	14	26	34	22	6	0	0	0.32	0.20
	2:1R	5	49	11	24	36	22	9	0	0	0.41	0.24
	1:2R	8	32	28	13	47	9	16	0	0	0.31	−0.25
	1:5R	6	31	29	7	53	5	24	0	0	0.45	−0.43
	5:1P	3	52	8	24	36	25	5	6	4	0.49	0.32
	2:1P	1	40	21	22	37	21	10	11	11	0.25	0.03
	1:2P	4	38	22	9	51	10	20	5	5	0.50	−0.26
	1:5P	2	26	34	4	56	6	30	3	2	0.51	−0.63
JF	5:1R	6	51	8	24	37	26	6	0	0	0.50	0.31
	2:1R	8	53	8	10	49	22	12	0	0	0.76	0.07
	1:2R	5	47	13	14	46	9	21	0	0	0.54	0.02
	1:5R	7	42	16	10	52	6	25	0	0	0.57	−0.15
	5:1P	2	59	1	42	18	25	4	0	1	0.70	1.07
	2:1P	4	54	6	21	39	24	12	5	3	0.61	0.34
	1:2P	1	55	6	18	41	10	22	6	5	0.66	0.30
	1:5P	3	50	9	19	42	5	25	6	7	0.54	0.20
LSS	5:1R	8	51	10	13	46	24	5	0	0	0.63	0.08
	2:1R	6	45	15	12	48	19	9	0	0	0.54	−0.06
	1:2R	7	45	15	13	47	11	20	0	0	0.52	−0.04
	1:5R	5	39	20	13	48	5	26	0	0	0.43	−0.14
	5:1P	4	47	12	20	41	26	6	8	7	0.45	0.14
	2:1P	2	52	8	21	39	21	11	6	6	0.54	0.27
	1:2P	3	52	9	19	40	9	21	4	6	0.54	0.22
	1:5P	1	30	29	9	52	6	22	8	6	0.39	−0.37

Table 3

(*Continued*)

Part.	Cond.	Order	B_{11}	B_{12}	B_{21}	B_{22}	R_{11}	R_{22}	P_{21}	P_{12}	log d	log b
MK	5:1R	2	42	18	26	34	22	4	0	0	0.24	0.13
	2:1R	4	26	23	20	31	11	8	0	0	0.12	−0.07
	1:2R	1	30	30	19	41	8	20	0	0	0.17	−0.17
	1:5R	3	21	39	11	49	6	26	0	0	0.19	−0.46
	5:1P	6	32	28	26	34	24	4	11	8	0.09	−0.03
	2:1P	8	37	23	18	42	21	10	9	10	0.29	−0.08
	1:2P	5	22	38	8	52	10	20	4	7	0.29	−0.53
	1:5P	7	30	31	8	51	5	24	6	3	0.40	−0.41
NC	5:1R	1	56	3	40	21	22	5	0	0	0.50	0.78
	2:1R	3	51	10	18	41	22	7	0	0	0.53	0.18
	1:2R	2	38	20	13	49	8	18	0	0	0.43	−0.15
	1:5R	4	34	25	18	44	4	25	0	0	0.26	−0.13
	5:1P	5	49	11	23	37	24	5	5	6	0.43	0.22
	2:1P	7	51	9	35	25	13	9	4	4	0.30	0.45
	1:2P	6	53	7	27	33	6	16	3	6	0.48	0.40
	1:5P	8	43	17	16	44	4	24	5	7	0.42	−0.02

The stimuli were 12 × 12 arrays (115 mm wide × 125 mm high) in the center of the white screen, with each position of the array occupied by either a blue or a red ''greeblie'' (measuring 8 mm wide and 9 mm high) against a white background. ''More blue'' stimuli consisted of 75 random array positions filled with blue greeblies and 69 random array positions filled with red greeblies. ''More red'' stimuli contained 75 random array positions filled with red greeblies and 69 random array positions filled with blue greeblies. Participants responded on a two-key response panel (with telegraph Morse keys) connected to the computer's USB port via a Lab Jack™ interface device. Beside the left key was a picture of a blue greeblie (indicating the response for ''more blue''), and beside the right key was a picture of a red greeblie (indicating the response for ''more red'').

Procedure

There were eight conditions in Experiment 3. Four conditions varied the reinforcer ratio without punishment for errors (similar to the R-only conditions in Experiment 2); the four ratios used were 5:1, 2:1, 1:2, and 1:5. These R-only conditions were labeled 5:1R, 2:1R, 1:2R, and 1:5R, respectively (Table 3). The distribution of reinforcers was varied using interdependent scheduling with the overall rate of reinforcement based on a VI 10-s schedule. Another four conditions also varied the reinforcer ratio (5:1, 2:1, 1:2, and 1:5), but included punishment for errors (similar to the R+P conditions in Experiment 2). These R+P conditions were labeled 5:1P, 2:1P, 1:2P, and 1:5P, respectively (Table 3). The distribution of punishers was held constant and equal (1:1) using interdependent scheduling, with overall rates of reinforcement and punishment based on VI 10-s schedules. For all conditions, SPP was set at .5. The difficulty levels for each condition were not titrated (i.e., all stimuli contained 75 greeblies of one color and 69 greeblies of the other).

Participants received one condition per session. Sessions were conducted no less than 24 hours apart and no more than one week apart. The presentation order of the conditions was partially counterbalanced across all the participants, with the constraints that all four R-only conditions and all four R+P conditions were sat consecutively, and that no two consecutive conditions arranged the greater reinforcer frequency on the same key (Table 3).

The general procedure and instructions were similar to those presented in Experiment 2. However, some additional feedback was presented during the consequence screens corresponding to the response made. If the participant made a correct left key (''more blue'') response and a reinforcer was scheduled for that response, a blue check (✓) appeared in the bottom left hand corner of the screen. Likewise, if the participant made a correct right key (''more red'') response and a reinforcer was scheduled, a red check appeared in the bottom right hand corner of the screen. For the R+P conditions, additional feedback was also presented when participants obtained a punisher. If the participant made an incorrect ''more blue'' or ''more red'' response and a punisher was scheduled for that response, a blue or red picture of a ''X'' appeared at the bottom of the screen, on the side corresponding to the response key they just pressed. For the R-only conditions, participants reached 70 points or 50 min to finish each session. For the R+P conditions, participants reached 50 points (net) or 50 min to finish each session.

Results and Discussion

Experimental sessions lasted approximately 30 to 40 min, with an average of 338 trails completed (*SD* = 75.0). The last 120 trials from each experimental condition were analyzed for each participant in the same manner as Experiment 1. Participant CY made zero B_{21} responses in the last 120 trials of Condition 1:5P; thus, a correction was made with $B_{21} = 0.5$ for calculations of log d and log b for that particular participant in that condition. These results are presented in Table 3.

Figure 6 plots estimates of log d (top) and log b (bottom) for each participant across the four relative reinforcer frequency variations (5:1, 2:1, 1:2, and 1:5) for the R-only (left) and R+P (right) conditions. Estimates of discriminability were more variable in Experiment 3 compared to those obtained in Experiments 1 and 2; this is most likely because task difficulty was not titrated in the present experiment. Mean discriminability did not differ systematically across the R-only conditions, $F(3,21) = 1.319$, $p = .30$, or R+P conditions however, $F(3,21) = 1.536$, $p = .24$, so the absence of a titration procedure appeared not to affect the overall findings. Again, this independence between discriminability and relative reinforcer frequency variations is consistent with Davison and Tustin's (1978) model of signal detection. Like Experiments 1 and 2, mean discriminability was slightly higher across R+P conditions ($M = 0.45$) than R-only conditions ($M = 0.35$), but a 4 (Reinforcer Ratio) × 2 (Condition Type) ANOVA found no significant effect of condition type, $F(1,14) = .824$, $p = .38$.

Figure 6 (bottom) shows that estimates of response bias were more variable for R+P conditions than R-only conditions. For the R-only conditions, estimates of response bias differed significantly across reinforcer ratios, $F(3,21) = 10.74$, $p < .001$. As with Experiment 1, individual estimates of sensitivity were calculated from each participant's response bias data for R-only conditions using least squares linear regression analyses. Positive slopes were found across all participants ($M = 0.31$), and a one-sample t-test found that these were significantly greater than zero, $t(7) = 4.578$, $p < .01$. Thus, participants were systematically biased towards the alternative associated with the higher rate of reinforcement. The mean slope was similar to the slope obtained with Group A of Experiment 1 (Figure 3, $M = 0.36$) which arranged similar conditions, and also with previous human detection research; for example, mean slope ranged between 0.33 to 0.36 across experiments in Alsop et al.'s (1995) study.

For the R+P conditions, estimates of response bias also differed significantly across reinforcer ratios, $F(3,21) = 7.633$, $p < .01$. Individual estimates of sensitivity were calculated from each participant's response bias data for R+P conditions using least squares linear regression analyses. Again, positive slopes were found across all participants ($M = 0.40$) with the possible exception of a negligible slope obtained by CM. A one-sample t-test also found that these slopes were significantly greater than zero, $t(7) = 3.860$, $p < .01$. Thus, on average, participants showed a greater preference towards the alternative associated with the higher rate of reinforcement when errors were punished occasionally than when they were not. This increase in mean sensitivity from reinforcer-only to reinforcer + punisher conditions is more consistent with a subtractive model of punishment than an additive model.

A closer analysis of the individual response bias data was performed to see if within-subject changes in sensitivity were consistent with the mean increase from R-only to R+P conditions. Figure 7 shows each individuals' response bias data across the four relative reinforcer frequency variations, and also displays the results from least

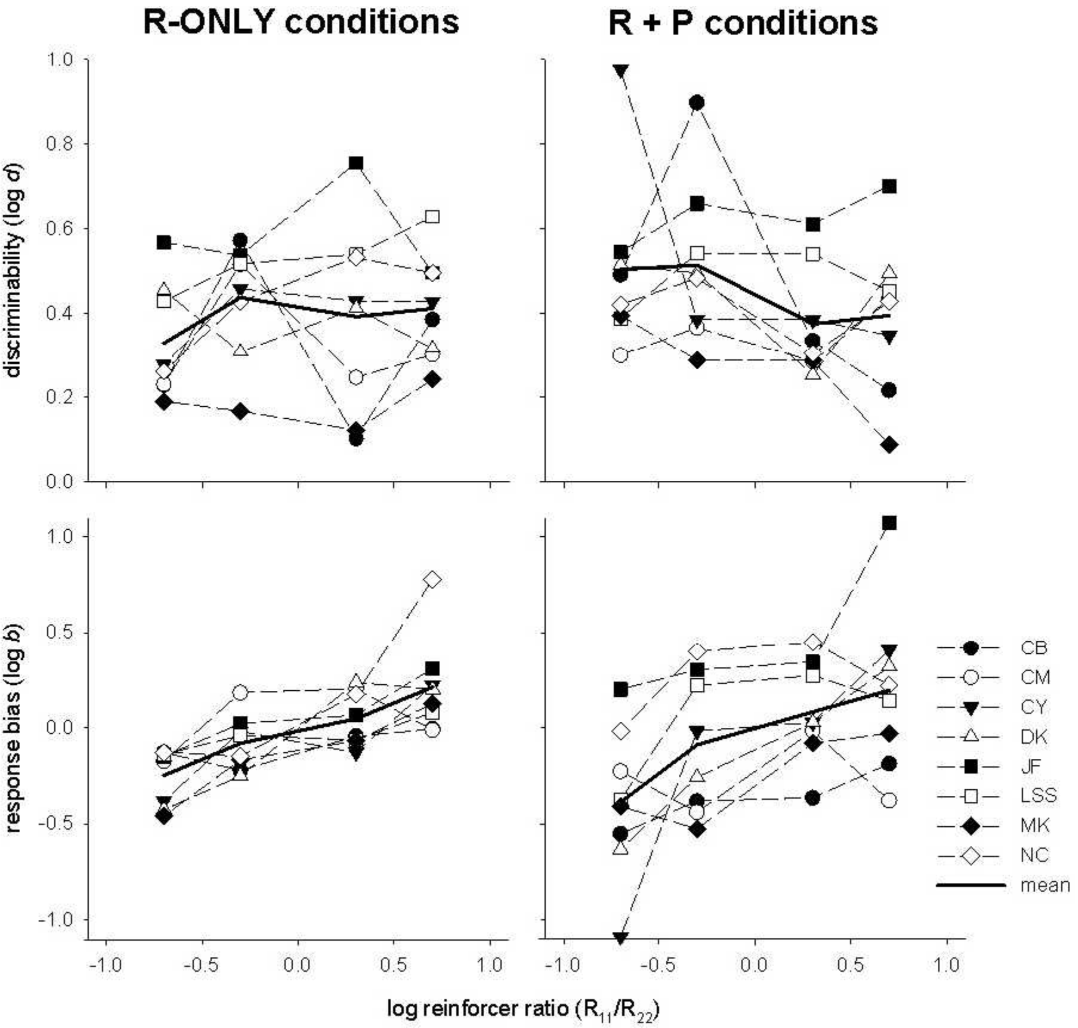

Fig. 6. Discriminability (log *d* – top) and response bias (log *b* – bottom) are plotted over changes in relative reinforcer frequency (log R_{11}/R_{22}) for the reinforcer-only conditions (left) and the reinforcer + punisher conditions (right) in Experiment 3. Individual participant data and the overall means are given.

squares linear regression analyses performed on each participant for both condition types for Experiment 3. Five participants (CB, CY, DK, JF, and LSS) showed increases in sensitivity from R-only conditions (filled circles) to R+P conditions (unfilled triangles), with reasonably good regression fits ($M = .79$). However, 3 participants (NC, CM, and MK) showed decreases in sensitivity from R-only to R+P conditions, but regression fits were quite poor (i.e., close to zero) for 2 of the 3 participants (NC, CM); only 1 participant (MK) showed a decrease in sensitivity with good regression fits. Again, the increases in sensitivity favor a subtractive punishment model, consistent with findings from the concurrent-schedules literature (e.g., Critchfield, et al., 2003; Farley, 1980).

There was, however, some evidence that the order in which participants received the R-only and R+P conditions affected performance. Participants CB, CM, MK, and NC received all four R-only conditions followed by the R+P conditions (Figure 7, left panels), with 3 participants showing lower sensitivity in R-only than R+P conditions (albeit 2 with poor regression fits). Mean sensitivity across these 4 participants was 0.31 for R-only conditions and 0.19 for R+P conditions. In contrast, all 4

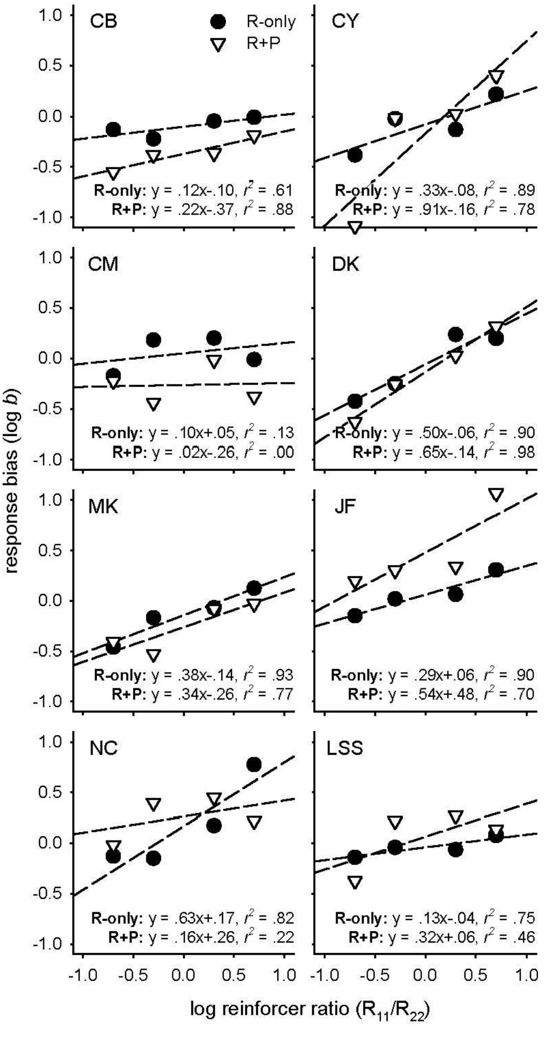

Fig. 7. Response bias (log *b*) is plotted over changes in relative reinforcer frequency (log R_{11}/R_{22}) separately for each participant in Experiment 3. Reinforcer-only conditions are presented as filled circles, while reinforcer + punisher conditions are presented as unfilled triangles. Results from least squares linear regression analyses are also presented for each participant for R-only and R+P conditions separately.

participants who received R+P conditions followed by R-only conditions (CY, DK, JF, and LSS—Figure 7, right) showed greater sensitivity with the inclusion of punishment (along with reasonable regression fits). Mean sensitivity for these participants was 0.31 for R-only conditions, and 0.61 for R+P conditions.

It is unclear why an order effect was found in the present experiment. However, a number of reasons were explored. First, it is possible that sensitivity to the reinforcer ratio decreased over the course of the experiment. In both cases, participants obtained lower estimates of sensitivity for the second condition type compared to the first condition type (0.31 to 0.19 for one group, 0.61 to 0.31 for the other). However, mean estimates of sensitivity for the R-only conditions were identical for both groups, and also consistent with Group A of Experiment 1 ($a = 0.36$) and previous research (e.g., Alsop et al., 1995); this consistency argues against a general overall decrease in sensitivity.

Second, the difference in sensitivities was perhaps related to differences in discriminability. Figure 6 (top) shows that participants who received R+P conditions first had higher estimates of discriminability than those who received the R+P conditions second; however, this difference was not significant. Furthermore, no significant correlations were found between estimates of sensitivity and estimates of discriminability for the R-only conditions ($r = -.05$, n = 8, $p = .92$) or the R+P conditions ($r = .47$, n = 8, $p = .23$).

Finally, previous concurrent schedule research (e.g., Alsop & Elliffe, 1988; Logue & Chavarro, 1987) has found that increases in overall reinforcer rate increased sensitivity. It is possible that changes in sensitivity in the present experiment were related to overall reinforcer or punisher rates. To investigate this, overall reinforcer and punisher rates were calculated for each condition, and 4 (Reinforcer Ratio) × 2 (Order) ANOVAs were performed on the R-only and R+P conditions separately. No significant difference in overall punisher rates was found for the R+P conditions, $F(1,6) = 0.062$, $p = .81$, however, the differences in overall reinforcer rates approached significance for the R+P conditions, $F(1,6) = 5.280$, $p = .06$, and was significant for the R-only conditions, $F(1,6) = 12.30$, $p < .05$. In both cases, participants who were presented with R-only conditions second received higher rates of reinforcement (R+P: M = 2.74 reinforcers/min; R-only: M = 2.96 reinforcers/min) than those who were presented with the R-only conditions first (R+P: M = 2.55 reinforcers/min; R-only: M = 2.63 rfrs/min). However, it seems unlikely that such a small difference in reinforcer rate (R+P = 0.19 reinforcers/min; R-only = 0.33 reinforcers/min) was sufficient to affect sensitivity, particularly since Alsop and Elliffe varied reinforcer rates between 0.22 and 10 reinforcers per minute to demonstrate an effect.

GENERAL DISCUSSION

The present experiments demonstrated that point-loss punishers for errors influenced human performance on detection tasks. Varying the relative frequency of point-loss punishment systematically biased participants away from responding on the alternative associated with the higher rate of punishment (Group B – Experiment 1). This was consistent with the predictions made by both additive and subtractive punishment versions of Davison and Tustin's (1978) GML-based model of signal detection (Figure 2, top). These results were also parallel but opposite to the effects of reinforcing correct responses with point gains (Group A – Experiment 1), which systematically biased participants towards the alternative associated with the higher rate of reinforcement; this was consistent with previous human detection research (Alsop, et al., 1995; Johnstone & Alsop, 1996).

The results from Experiments 2 and 3 found that point-loss punishers also had an effect on preference for the more reinforced alternative. In both experiments, there was some evidence for increases in preference for the more reinforced alternative when a constant and equal rate of punishment was superimposed onto two response alternatives. However, order effects were found in both experiments. In Experiment 2, a general increase in sensitivity across the three sessions cannot be ruled out, although some reversal of the effects of punishment was found with Order 1 (R-only, R+P, R-only), and significant increases were found from R-only to R+P conditions. In Experiment 3, although 5 of the 8 participants obtained higher sensitivity estimates for R+P conditions than R-only conditions (consistent with a subtractive model of punishment), 4 of the 5 participants received R+P conditions first followed by R-only conditions. While previous researchers (Critchfield, et al., 2003; Farley, 1980) presented R-only conditions first followed by R+P conditions, 3 of the 4 participants in Experiment 3 (of the present set of studies) who received conditions in this order showed decreases in sensitivity; that is, the opposite finding to previous studies. Thus, it appears that condition order may also play some part in the effects of punishment on sensitivity. The effects of condition order on detection and choice task performance may warrant further investigation.

Together, the data from Experiments 2 and 3 provide greater support for a subtractive punishment version over an additive punishment version of Davison and Tustin's (1978) GML-based model of signal detection performance (Figure 2). This result is consistent with findings using concurrent-schedule choice procedures, where there is overwhelmingly more support for a subtractive model of punishment (e.g., Critchfield, et al., 2003; de Villiers, 1980; Farley, 1980) over an additive model of punishment (Deluty, 1976). In fact, only Deluty (1976; but see also Deluty, 1982; Deluty & Church, 1978) has claimed support for an additive model of punishment. A closer look at Deluty's (1976) experiment however, shows that the conditions he ran were not adequate to directly compare the additive and subtractive models. A reanalysis of Deluty's data by de Villiers (1980) showed that the subtractive model accounted for a similar amount of the variance in Deluty's data as the additive model; that is, both models made nearly identical predictions for Deluty's conditions. Thus, there appears to be very little support for an additive model of punishment, and the findings from the present experiments extend the support for the subtractive model of punishment beyond that of the simple concurrent-schedule choice procedure to the signal-detection choice procedure.

While Davison and Tustin's (1978) model appeared to capture the effects that punishment had on the participants' behavior quite well, Alsop and Davison (Alsop, 1991; Alsop & Davison, 1991; Davison, 1991) and Davison and Nevin (1999) have proposed a competing model of detection performance based on the discriminability (or confusability) of stimulus–response and response–reinforcer contingencies. The contingency-discriminability model addresses the lack of parameter invariance sometimes found with Davison and Tustin's model by using two independent parameters – one which measures the discriminability between the stimulus-response contingency (termed d_s or d_{sr}) and another which measures the discriminability between the response–

reinforcer contingency (termed d_r or d_{rr}). However, the independence of d_s and d_r has also received mixed support, with some studies finding an interaction between d_s and d_r and others finding no relation (see Alsop & Porritt, 2006 for a summary). Furthermore, it is unclear how punishers should be incorporated into the contingency-discriminability model. For example, will the discrimination of response-reinforcer and response–punisher contingencies require the same parameter or separate parameters? Likewise, is discriminability between the stimulus–response contingencies similar or different following a reinforcer or a punisher? Even with the assumption that d_s and d_r are identical for reinforcers and punishers, the simplest additive and subtractive punishment versions of the Alsop-Davison-Nevin model make similar predictions to the additive and subtractive versions of the Davison and Tustin model (Figure 2). As it currently stands, the integration of reinforcer and punisher effects in detection models appears less complex with the GML-based Davison and Tustin model compared to the Alsop-Davison-Nevin contingency-discriminability model.

The present experiments found an independence between estimates of discriminability and changes to the reinforcer or punisher contingencies, consistent with the parameter invariance assumption from the Davison and Tustin (1978) model. However, there was some evidence that discriminability was higher in conditions where punishment for errors was included (R+P conditions) than conditions with no punishment (R-only conditions; Experiments 1 and 2); the additive or subtractive versions of the Davison and Tustin model (Equations 6 to 11) do not predict this finding. It is possible that punishers improve discriminability by altering motivation or attention. A recent model proposed by Nevin, Davison, and Shahan (2005) integrates the Alsop-Davison-Nevin (Alsop & Davison, 1991; Davison & Nevin, 1999) contingency-discriminability model with a theory of attending. Nevin et al. proposed that the probability of attending to the sample stimuli (S_1 and S_2) and comparison stimuli (termed C_1 and C_2 for the stimuli signaling the B_1 and B_2 responses, respectively) in a detection task is positively related to the reinforcer rate, in a manner similar to behavioral momentum theory (Nevin & Grace, 2000). Although Nevin et al.'s model deals explicitly with the effects of reinforcement on attention, it is unclear how the effects of punishers should be integrated into such model. Does the inclusion of punishment for errors increase the probability of attending to the sample and/or comparison stimuli? If so, does the increase in discriminability (log *d*) found for R+P conditions in the present experiments imply that reinforcement and punishment combine additively to increase the probability of attending beyond the effects of reinforcement alone? This might be a challenge for any model based on the reinforcer effects encompassed by behavioral momentum. Given how little is known about the effects of punishment on attention, this may be a worthwhile direction for future research.

The present series of experiments is the first systematic investigation of the effects of punishment on human signal-detection performance, and there are some limitations with areas for improvement. For example, due to time limitations and monetary constraints, participants only received one session per condition while previous studies of choice and punishment (e.g., Critchfield, et al., 2003; Farley, 1980) arranged a number of sessions per condition. A larger range of ratios may have also been better suited to the differing additive and subtractive model predictions, as the deviations from linearity are predicted by the subtractive model at extreme ratios (Figure 2, dashed line). Future directions for research may include studying other punisher types (e.g., response effort, timeout), and comparisons between human and nonhuman detection performance. Because punishers are real consequences in many everyday situations (e.g., quality control and medical screening both have positive consequences for correct choices and negative consequences for errors), research on the interaction between reinforcement and punishment is thus important on both theoretical and applied grounds.

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