

The generalization-across-dimensions model applied to conditional temporal discrimination

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Abstract

Can simple choice conditional-discrimination choice be accounted for by recent quantitative models of combined stimulus and reinforcer control? In Experiment 1, two sets of five blackout durations, one using shorter intervals and one using longer intervals, conditionally signaled which subsequent choice response might provide food. In seven conditions, the distribution of blackout durations across the sets was varied. An updated version of the generalization-across-dimensions model nicely described the way that choice changed across durations. In Experiment 2, just two blackout durations acted as the conditional stimuli and the durations were varied over 10 conditions. The parameters of the model obtained in Experiment 1 failed adequately to predict choice in Experiment 2, but the model again fitted the data nicely. The failure to predict the Experiment 2 data from the Experiment 1 parameters occurred because in Experiment 1 differential control by reinforcer locations progressively decreased with blackout durations, whereas in Experiment 2 this control remained constant. These experiments extend the ability of the model to describe data from procedures based on concurrent schedules in which reinforcer ratios reverse at fixed times to those from conditional-discrimination procedures. Further research is needed to understand why control by reinforcer location differed between the two experiments.

KEYWORDS

choice, conditional discrimination, generalization, location control, quantitative modeling, temporal control

Behavior depends not only on its consequences (reinforcer control) but also on the stimulus conditions in which behavior and consequences occur (stimulus control). Reduction in either reinforcer control or stimulus control has functionally similar effects on the degree to which the environment exerts discriminative control over behavior (see Davison & Nevin, 1999). Further, both stimulus and reinforcer control are necessary for the development of discriminative behavioral control by the structure of an environment. Failure to respond differentially in differing stimulus conditions—to discriminate—will occur because (1) of a physiological inability to differentiate the stimuli, (2) the reinforcer conditions in the two stimuli do not differ, or (3) different reinforcer conditions between the two stimuli cannot be discriminated. Thus, differential behavioral control with respect to stimuli and reinforcer

contingencies requires both stimulus and reinforcer discrimination, and the absence of just one of these will lead to a failure of discriminative control (see, for example, Alsop & Davison, 1991; Miller et al., 1980).¹ Despite the interdependence of reinforcer and stimulus control, research has tended to focus on just one of these two aspects of control, with the other arranged to be maximally discriminable. However, over the last 45 years, our program of research has attempted to understand how

¹A reviewer pointed out that a long-term *change* in reinforcer contingencies may change behavior in the absence of any discriminative-stimulus change. If the animal shows a change in behavior, this implies that the change in reinforcer conditions would have been detected in the presence of unchanged but operative stimulus control, which could be shown by comparing generalization gradients before versus after the contingency change. It would not be a case of changed contingencies leading to a change in behavior in the absence of stimulus control.

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stimulus conditions and obtained reinforcers combine in single quantitative models to control behavior. Initially, research in this program was focused on conditional-discrimination procedures (known as the Yes–No procedure in signal-detection research); more recently, our research has focused on more complex continuous procedures in which different stimulus conditions signal different changes in reinforcer conditions across time since a marker event.

Over this period, the specific quantitative models used to understand behavior have evolved in the face of new empirical evidence (for the major theoretical developments, see Cowie & Davison, 2020; Davison & Cowie, 2022; Davison & Jenkins, 1985; Davison & Nevin, 1999; Davison & Tustin, 1978). Rather than detailing this history, here we focus on the latest iteration of the model as offered by Cowie and Davison (2020) and by Davison and Cowie (2022). Using a discrete-trial procedure with pigeons, Davison and Cowie arranged that a single reinforcer would become available on a variable-interval (VI) 45-s schedule in each trial. The probability that the reinforcer would be arranged on one of two keys changed from .1 to .9 or from .9 to .1 at 30 s after the trial started, and which of two probability sequences was arranged on a trial ($p = .5$) was signaled by two differing yellow/green flash frequencies. The physical difference between the stimuli signaling the sequences was varied across conditions (see their Table 1). Log response ratios generally followed the signaled change in reinforcer probability across time in trials, but the amount of change depended on the physical difference between the signaling stimuli, with no change occurring when the stimuli were similar but not identical. To capture these results, Davison and Cowie suggested a model comprising two major assumptions. First, because of less than perfect temporal discrimination, reinforcers delivered at each time since trial start generalize according to an assumed Gaussian distribution to adjacent times. The *apparent* reinforcers (R') at each time are the summation of reinforcers at that time not generalized to another time and of reinforcers from other times generalized to

that time. Thus, in the t^{th} time bin of n time bins analyzed, R'_t is

$$R'_t = \sum_n^1 \left[R_n \left(\frac{e^{-.5 \left(\frac{t-n}{\sigma_{s,n}} \right)^2}}{\sqrt{2\pi\sigma_{s,n}}} \right) \right], \quad (1)$$

where R denotes the number of reinforcers obtained and $\sigma_{s,n}$ is the standard deviation of time estimation in the n^{th} bin. A standard deviation that increases in direct proportion to the time to be discriminated is the same assumption as is made in scalar-expectancy theory (Gibbon, 1977; Gibbon & Church, 1981). The scalar property of time would suggest that $\sigma_{s,n}$ would increase linearly across time, but Cowie and Davison reported that an ogival function fitted the data better than a linear increase.

The second assumption was that there can be confusion between the two response-reinforcer alternatives (as discussed by Davison & Nevin, 1999), and this was modeled in the same way as in Davison and Nevin. If m_t denotes the relative discrimination accuracy of the response that provides reinforcers ($.5 < m < 1$) in time t since a marker event, then

$$R''_{1,t} = m_t R'_1 + (1 - m_t) R'_{2,t}, R''_{2,t} = m_t R'_{2,t} + (1 - m_t) R'_{1,t}. \quad (2)$$

Thus, the apparent reinforcer frequency after response-reinforcer confusion (R'') modulates the apparent frequency after temporal confusion (R'). Cowie and Davison (2020) found that response-reinforcer discrimination did not remain constant with respect to time since trial start but rather decreased (or as they put it, spatial generalization increased) according to an ogival function of time. Similar results were reported by Davison and Cowie (2022).

In the general case, if m_t is some function of time since the marker event, the model used by Cowie and Davison (2020) and Davison and Cowie (2022) to predict log response ratio ($\log[B_{1t}/B_{2t}]$) at each time bin t of n total time bins was

$$\log \frac{B_{1t}}{B_{2t}} = \log \left(\frac{m_t \sum_n^1 \left[R_{1,t} \left(\frac{e^{-.5 \left(\frac{t-n}{\sigma_{s,n}} \right)^2}}{\sqrt{2\pi\sigma_{s,n}}} \right) \right] + (1 - m_t) \sum_n^1 \left[R_{2,t} \left(\frac{e^{-.5 \left(\frac{t-n}{\sigma_{s,n}} \right)^2}}{\sqrt{2\pi\sigma_{s,n}}} \right) \right]}{m_t \sum_n^1 \left[R_{2,t} \left(\frac{e^{-.5 \left(\frac{t-n}{\sigma_{s,n}} \right)^2}}{\sqrt{2\pi\sigma_{s,n}}} \right) \right] + (1 - m_t) \sum_n^1 \left[R_{1,t} \left(\frac{e^{-.5 \left(\frac{t-n}{\sigma_{s,n}} \right)^2}}{\sqrt{2\pi\sigma_{s,n}}} \right) \right]} \right) + \log c. \quad (3)$$

Notice that both σ_s and m are subscripted n and t , respectively, allowing both these parameters to change with time since a marker event, as suggested by Cowie and Davison (2020) and Davison and Cowie (2022). The bias parameter $\log c$ is, as in the generalized matching relation (Baum, 1974), a supposedly constant parameter that measures preference for one choice alternative that is unaccounted for by experimentally manipulated reinforcer parameters. Sources of such preference are variables that are constant throughout the experiment, such as response force differences between response keys.

$$(1 - m_t) \rightarrow \frac{e^{-.5 \left(\frac{L_1 - L_2}{\sigma_L} \right)^2}}{\sqrt{2\pi\sigma_L}}$$

We will take location standard deviation σ_L as the same for the two locations at each time, but this is a simplifying assumption that may not hold in all cases. Thus, after algebraic simplification, the model for choice in each bin t since a marker event that we will use here is

$$\log \frac{B_{1t}}{B_{2t}} = \log \left(\frac{\left[\sum_n \left[R_{1n} \left(\frac{e^{-.5 \left(\frac{L_1 - L_2}{\sigma_{s,n}} \right)^2}}{\sqrt{2\pi\sigma_{s,n}}} \right) \right] + \frac{e^{-.5 \left(\frac{L_1 - L_2}{\sigma_{L,t}} \right)^2}}{\sqrt{2\pi\sigma_{L,t}}} \sum_n \left[R_{2n} \left(\frac{e^{-.5 \left(\frac{L_1 - L_2}{\sigma_{s,n}} \right)^2}}{\sqrt{2\pi\sigma_{s,n}}} \right) \right]}{\left[\sum_n \left[R_{2n} \left(\frac{e^{-.5 \left(\frac{L_2 - L_1}{\sigma_{s,n}} \right)^2}}{\sqrt{2\pi\sigma_{s,n}}} \right) \right] + \frac{e^{-.5 \left(\frac{L_2 - L_1}{\sigma_{L,t}} \right)^2}}{\sqrt{2\pi\sigma_{L,t}}} \sum_n \left[R_{1n} \left(\frac{e^{-.5 \left(\frac{L_2 - L_1}{\sigma_{s,n}} \right)^2}}{\sqrt{2\pi\sigma_{s,n}}} \right) \right]} \right) + \log c. \tag{4}$$

Equation 3 describes the reallocation of reinforcers between response keys in a different way from the redistribution of reinforcers across time. However, the data from Davison et al. (2020) suggested that reinforcers were redistributed between responses (in their case, saccadic latencies) rather than reallocated. Reallocation implies that all reinforcers lost from one response are allocated to the other response, whereas redistribution implies that reinforcers may be allocated to nonmeasured locations. Both Davison et al.'s data and model parsimony suggest that reinforcers should be redistributed across whatever dimension that defines effective responding, such as saccadic latency, location in space, and points on an exteroceptive stimulus dimension. We propose here to remedy this inconsistency in dealing with response location in the model that we have previously used, and that was a feature, for both responses and stimuli, of the model proposed by Davison and Nevin (1999). Thus, for the present research, if L_1 and L_2 are the response-location definitions and σ_L is the standard deviation of the Gaussian generalization around each location, we will replace m_t across time with

$$m_t \rightarrow \frac{e^{-.5 \left(\frac{L_1 - L_1}{\sigma_L} \right)^2}}{\sqrt{2\pi\sigma_L}} = \frac{1}{\sqrt{2\pi\sigma_L}},$$

with an equivalent equation for L_2 . We replace $(1 - m_t)$ across time in Equation 3 with

We retain the temporal subscripts t for σ_L (location standard deviation) and n for σ_s (temporal standard deviation) because previous research has suggested that both m and σ_s when analyzed using the previous model (Cowie & Davison, 2020; Davison & Cowie, 2022) changed as a function of time—this would be expected for σ_s , according to the scalar theory of timing (Gibbon, 1977).

The changes across time in locational control m (Equation 3) and temporal control σ_s that we previously reported (Cowie & Davison, 2020; Davison & Cowie, 2022) could have resulted from m being modeled using Equation 3. Thus, in the analysis of the Experiment 1 results we propose to replace Equation 3 with Equation 4. For locational generalization, we used location placeholders (L_1, L_2) of -100 and $+100$ because the two response keys were 200 mm apart in the present experiments. The approach described in Equation 4 clarifies the model as a clearly multidimensional generalization model. We will call this model the generalization across dimensions model.

The structure of our model of the combined control by discriminative stimuli and reinforcers has changed radically since it was first proposed (Davison & Tustin, 1978; Davison & Nevin, 1999), and we have developed recent models using procedures quite different from simple conditional-discrimination arrangements with which we started. Therefore, it is time to ask whether this general approach to modeling is able to understand simpler conditional-discrimination procedures and whether the modified model can provide

any additional insights. Thus, we designed two conditional-discrimination experiments. **Experiment 1** had some similarity to our recent research in that one choice response following one of a set of smaller time intervals was occasionally followed by reinforcers, whereas a different response following one of a set of longer time intervals was occasionally reinforced. The procedure was further simplified in **Experiment 2** in which we presented just two time intervals—a standard temporal conditional-stimulus experiment. Our expectation was that the model would provide a satisfactory fit to the **Experiment 1** data and that the model, when applying parameter values estimated from fits to the **Experiment 1** data, would accurately predict the **Experiment 2** data.

EXPERIMENT 1

In **Experiment 1**, each trial consisted of the presentation of an interval drawn from 10 different intervals followed by a two-key choice; a response to one key was deemed correct if one of the shorter five intervals had been presented, and a response to the other key was correct if one of the longer five intervals had been presented. Across conditions, we varied the distribution across time that determined the 10 intervals.

Similar experiments have previously been reported. Stubbs (1976) asked pigeons to report which of two sets of light durations had been presented, the shorter duration set being 11–15-s durations in 1-s steps, the longer being 16–22 s in 1-s steps. He varied the relative reinforcer rate for correct responses across six conditions. Choice ratios undermatched reinforcer ratios as expected from generalized matching (Baum, 1974; Davison & Tustin, 1978) as shown in Stubbs's Figure 3, and choice changed progressively across both stimulus duration and relative reinforcer frequency (Stubbs's Figure 1). In similar research, McCarthy and Davison (1986) asked pigeons to report a fixed duration (5 to 55 s in 5-s steps across conditions) by pecking one key or one duration within a set of variable durations (2.5–57.5 s in 5-s steps in every condition) by pecking another key. The results of manipulating the fixed duration value while keeping the variable durations constant were systematic (see McCarthy and Davison's Figure 3; see also Davison, 1989) with maximum preference of the fixed-duration key at the fixed-duration value. No quantitative model was offered. Unfortunately, the raw data from the above experiments are no longer available and thus cannot be used to assess the ability of the present model to account for temporal discrimination data more generally.

Subjects

Six pigeons, numbered 21 to 26, started **Experiment 1**. All pigeons had previously served in the experiment

reported by Cowie and Davison (2020), so no further training was required. The pigeons were weighed around 9.30 a.m. each day and given sufficient postsession mixed grain to maintain their body weights at 85% (± 15 g) of their free-feeding weights.

Apparatus

The apparatus was the same as used by Cowie and Davison (2020). Briefly, the pigeons worked in their individual home cages (375 mm high and deep and 370 mm wide), each of which was fitted with two wooden perches situated 60 mm above the grid floor, one being parallel to the rear wall, and one at 90 degrees to the rear wall. Three 20-mm diameter plastic response keys set 100 mm apart and 200 mm above the floor were located on the right-hand wall. These could be transilluminated yellow or red, and responses to these keys exceeding about 0.1 N were recorded. A 40- \times 40-mm food aperture was beneath the center key and 60 mm above the perch and provided access to a hopper containing wheat. The aperture was illuminated white, and the response keys were extinguished when the hopper was raised for 2.5 s. During experimental sessions, the pigeons could see other pigeons working on different experiments in the vivarium. Water and grit were available at all times.

Procedure

The lights in the experimental room were turned on at midnight and extinguished at 4 p.m. daily; experimental sessions commenced at 1 a.m. No one entered the room during experimental sessions. Experimental sessions started with the center response key being illuminated yellow and ended in blackout after 60 min or after 60 food deliveries had been obtained, whichever occurred first.

In **Experiment 1**, using a conditional-discrimination procedure, we asked pigeons to report from which of two, five-item sets of blackout durations the blackout duration on a trial came. The sets of durations were taken from the first five (S1, shorter blackout durations) and the second five (S2, longer blackout durations) of a 10-item sequence of increasing durations (Table 1; Figure 1). On each trial, the center key illuminated yellow and a single response to it turned the yellow key off and started a period of blackout. The blackout period ended with the two side keys (choice keys) being illuminated yellow. A single response to one of these keys extinguished the choice keys; the correct choice response depended on the duration of the preceding blackout. Thus, the length of the blackout following center-key pecks constituted two sets of temporal-interval stimuli (S1 or S2).

Correct choice responses were intermittently reinforced according to a dependent scheduling procedure; after each reinforcer, the next available reinforcer was

TABLE 1 Procedural settings in [Experiment 1](#).

Cond	Type	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	RFS	Sess.
1	Log	1.00	1.40	1.96	2.74	3.84	5.38	7.53	10.54	14.76	20.66	L-R	47
2	Lin	1.00	3.18	5.36	3.04	9.72	11.90	14.08	16.26	18.44	20.62	R-L	63
3	Rev Log	1.00	6.90	11.12	14.13	16.28	17.82	18.92	19.7	20.26	20.66	L-R	50
4	Sym Close	3.42	5.85	7.30	8.46	9.50	10.5	11.54	12.7	14.15	16.58	R-L	76
5	Sym Wide	1.00	3.43	4.88	6.04	7.08	12.92	13.96	15.12	16.57	19.00	L-R	60
6	Close Long	1.00	3.43	4.88	6.04	7.08	17.00	17.50	18.00	18.50	19.00	R-L	66
7	Close Short	1.00	1.50	2.00	2.50	3.00	12.92	13.96	15.12	16.57	19.00	L-R	69

Note: D1 to D5 and D6 to D10 are the two sets of blackout durations in seconds arranged. Correct responses following D1 to D5 were arranged to be on the left key if the RFS column was L-R and on the right key if RFS was R-L. Type is a verbal description of the arrangement of the blackout durations across the sets of blackouts. Sess. is the number of sessions training on each condition.

allocated to a correct response on a key with a probability of .5 and remained available until it was taken. Incorrect responses to the choice keys resulted in a 2.5-s blackout. Correct responses were followed by 2.5 s of access to food if a reinforcer was allocated to that correct response; if no reinforcer was allocated for the correct response on a trial, then the correct response produced a 2.5-s blackout. Following a food delivery or a blackout, the center key was illuminated yellow and the next trial commenced. This scheduling procedure (technically, a dependent-schedule conditional discrimination) resulted in approximately equal numbers of reinforcers being obtained following the presentation of exemplars of each stimulus set and more correct responses emitted than reinforcers obtained.

Across conditions in [Experiment 1](#) (Table 1), the way in which the 10 intervals comprising the S1 and S2 sets were distributed was varied to provide a comprehensive test of the model in Equation 4. Thus, across S1 and S2, the blackout intervals increased logarithmically in Condition 1 and linearly in Condition 2. In Condition 3, they increased according to a reversal of a logarithmic sequence. In Conditions 4 and 5, the intervals were arranged symmetrically around the mean of the intervals and distant from the mean or close to the mean, respectively. In Condition 6, we arranged the same intervals in S1 as in Condition 5 but with a closely packed set of longer intervals in S2. In Condition 7, we arranged the same S2 intervals as in Condition 5, but with a closely packed set of shorter intervals in S1. Together, these conditions provided a comprehensive variation of the way in which the varied durations were located in time in a trial, from linearly to more densely at shorter times than longer times (and vice versa), whether the two sets were close or far apart, and whether they were closely packed at shorter or longer times.

Conditions ran until weekly data analyses showed that choice had fully stabilized, showing small and inconsistent trends across weekly analyses of the last 15 sessions' data for each pigeon. To enhance behavioral control and the detection of condition changes, we varied the choice-response locations for correct responses

following S1 and S2 across conditions. The data we collected were the times in session at which all responses, stimulus changes, blackouts and food deliveries occurred. We analyzed the last 15 sessions' data from each condition.

Results

Figure 1 shows the group-average choice \log_{10} ratios of responding to the Left and Right keys ($\log_{10}[B_L/B_R]$) across the last 15 sessions of each condition as a function of blackout duration for each pigeon in [Experiment 1](#), and Appendix [Figures A1–A7](#) show the same data for the six individual pigeons. Individual pigeon data followed the same general pattern shown in Figure 1, and thus the group data shown in Figure 1 were representative of the individuals. As shown in Figure 1, choice changed progressively as a function of blackout duration in each condition except Conditions 6 and 7 in which the temporal distance from the longest S1 blackout duration to the shortest S2 duration was large. In Conditions 6 and 7, choice following S2 was approximately constant. Inter alia, this would be expected from any scalar-timing model in which the standard deviations of temporal estimates increased with duration: choice at long durations would be unaffected by the smaller standard deviations at shorter durations, whereas shorter durations would be affected by the larger standard deviations for longer time estimates.

Modeling

In our previous modeling of the joint effects of reinforcers delivered at times and at locations since a marker event, we arranged continuous concurrent VI schedules and thus were able to analyze choice (\log_{10} Left/Right response ratios) in fixed-duration time bins since the trial-start marker (the previous reinforcer). In the present experiment, only 10 different blackout durations were arranged such that we had only 10 time durations at

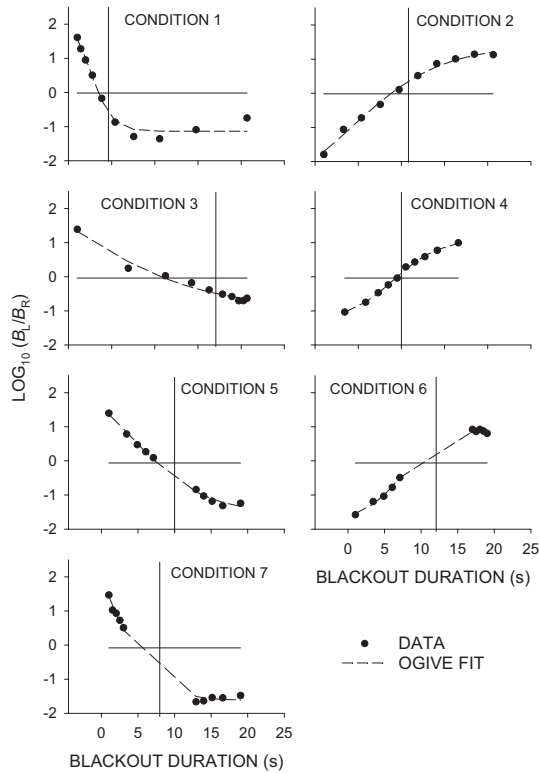


FIGURE 1 Data averaged across the six pigeons in each condition of Experiment 1 and fits of a descriptive ogive (Equation 5) to these data. The horizontal line denotes zero log response ratio (equal choice), and the vertical line shows the geometric mean of all 10 blackout intervals comprising S1 and S2. Data and ogive fits for individual pigeons are shown in Figures A1 to A7.

which choice could be measured and at which food deliveries could be obtained. In its basic form, the model we espoused has eight free parameters, so fitting it to the data from a single condition would be poor practice. Thus, we fitted the model to all data from the seven conditions (70 data points) for each pigeon. All models were fitted to data using the evolutionary method in the Microsoft Excel Solver.

Initial exploratory model fits to the current data set revealed that the model fitted poorly when the bias term, $\log c$, was kept constant across experimental conditions. Fits to the data were considerably enhanced by allowing for different $\log c$ values for each condition. Thus, $\log c$ values in Equation 4 were allowed to vary across conditions, creating different $\log c$ values for each condition.

In our first model assessment we used a model in which we assumed that σ_s and σ_L changed as a linear function of time with an intercept, thus 11 free parameters (seven $\log c$ values, two linear intercepts, and two linear slopes) for the 70 data points. However, this model produced negative-sloped linear changes in σ_L , which was untenable because it meaninglessly predicted that location standard deviations would become negative at longer times. A function that avoids this prediction is a hyperbola of the form $\sigma_{L,t} = \sigma_L(k) \times \sigma_L(h) / (\sigma_L(h) + t)$,

where $\sigma_L(h)$ is the half-life of the hyperbola, $\sigma_L(k)$ is the starting asymptote, and t is the blackout duration. Although other functions would also avoid the untenable prediction of negative standard deviations, we arbitrarily decided to use this hyperbola to describe the changes of σ_L across time. In the linear model assessment, we found that σ_s increased linearly across blackout duration with a slope of $\sigma_s(S)$ and intercept $\sigma_s(I)$. For these fits there were again 11 free parameters.

The model, assuming the same linear changes in σ_s and the same hyperbolic changes in σ_L with blackout duration but with specific $\log c$ parameters for each condition, provided an excellent description of the individual data and the data averaged across pigeons, with an average 95% of the variance accounted for in the 70 data points for the individual pigeons (Table 2). Figure 2 shows obtained log response ratios as a function of model-predicted log response ratios for all conditions and pigeons—the data mostly fell close to the line of perfect prediction, though some data points for Pigeon 26 deviated quite substantially. The deviating data came from blackout durations at which the pigeons made very few errors, so choice measures were likely poorly estimated. The values of $\sigma_L(k)$ and $\sigma_L(h)$ (Table 2), which hyperbolically determined σ_L , were reasonably consistent across pigeons, but Pigeon 25 was an outlier with different parameters for location. Similarly, the values of $\sigma_s(I)$ and $\sigma_s(S)$, which linearly determined σ_s , were reasonably consistent, with Pigeon 23 returning a nonzero value of the intercept $\sigma_s(I)$ and a smaller slope $\sigma_s(S)$. The value of $\sigma_s(I)$ was limited to being ≥ 0 because an intercept < 0 would not be tenable, and in general a value of 0 would have sufficed. Indeed, had we assumed this and used one fewer free parameter in our modeling, we would have increased the AIC value for all pigeons except for Pigeon 23. The obtained $\sigma_s(s)$ value for all pigeons was greater than zero (mean = 0.32), indicating increasing generalization across time, consistent with linear increases in error discriminating progressively longer durations (Gibbon, 1977).

The current model was preferable to our previous models in terms of logic and consistency with previous research. Was the current model a better descriptor of our data than our previous model (Equation 3) or some simplification of our current model? According to Burnham and Anderson (2004; see also Navakatikyan & Davison, 2010), a difference in Akaike-criterion values (ΔAIC) of < 6 indicates no differential support for either model, between 6 and 10 indicates strong support for the model with the lower Akaike value, and > 10 indicates no support for the model with the higher (more positive) value. Table 2 shows that on the ΔAIC criterion, the current model was exclusively supported over the previous (Davison & Cowie, 2022) model for Pigeons 21 and 25 and was strongly supported for Pigeon 22. For the other three pigeons, the two models did not differ in how well they described the data.

TABLE 2 Fits to Equation 4 using a linear change in σ_s and a hyperbolic change in σ_L across time for each pigeon and for the data averaged across pigeons. Also shown are the Akaike criterion (AIC) values for three comparison models.

	Pigeon						Mean
	21	22	23	24	25	26	
σ_L (k)	268.35	248.11	130.87	370.49	23.15	128.45	72.86
σ_L (h)	0.31	0.20	0.28	0.15	4.66	0.49	0.78
σ_s (I)	0.00	0.00	0.36	0.00	0.00	0.00	0.00
σ_s (S)	0.35	0.37	0.23	0.36	0.31	0.31	0.34
Log c1	0.09	-0.18	-0.36	0.14	-0.12	-0.29	-0.13
Log c2	0.34	0.19	0.12	0.09	-0.14	0.11	0.10
Log c3	-0.05	-0.14	-0.31	-0.01	-0.20	-0.23	-0.16
Log c4	0.19	0.30	-0.11	-0.09	-0.36	-0.09	0.05
Log c5	-0.27	-0.18	-0.42	-0.05	-0.24	-0.13	-0.21
Log c6	0.29	0.19	0.43	-0.39	0.00	0.41	0.11
Log c7	-0.49	-0.45	-0.76	-0.58	-0.41	-0.59	-0.52
VAC	0.97	0.95	0.95	0.92	0.94	0.96	0.98
AIC	-202	-193	-183	-152	-172	-186	-273
<i>AIC from comparison models</i>							
Const Log c	-156	-166	-148	-103	-141	-156	-207
Const σ_L	-159	-164	-157	-129	-167	-156	-214
DC (2022)	-190	-185	-185	-156	-146	-189	-242

Note: σ_L (k) and σ_L (h) indicate the values for the hyperbola that related σ_L to the blackout duration d as $\sigma_L = \sigma_L(k) \times \sigma_L(h) / (\sigma_L(h) + d)$. The parameters σ_s (I) and σ_s (S) indicate the intercept and slope relating σ_s to d as $\sigma_s = \sigma_s(I) + \sigma_s(S) \times d$. Log c1 to log c7 are the Left/Right-key bias for each experimental condition, VAC is the proportion of data variance accounted for (70 data points) by fits across all seven conditions, and AIC is the value of the Akaike criterion. For the comparison models, “Const Log c ” is a model that used a single log c value across all conditions, “Const σ_L ” is the model in which this parameter was held constant across blackout durations, and “DC (2022)” is the model (Davison & Cowie, 2022) in which both m and σ_s changed ogivally across time.

The model in which log c remained constant over conditions was conclusively rejected for all pigeons (Table 2). We also carried out an assessment of a model in which σ_L was constant across blackout duration. As Table 2 shows, this model was rejected for all except Pigeon 25 for which neither model was preferable (Table 2). We conclude that the present model is preferable to our previous model or any simpler models based on logic, research consistency, and Akaike-criterion values.

Discussion

The analyses of the Experiment 1 data supported the base model (Equation 4) in which Gaussian distributions generalized obtained reinforcers across both the blackout-duration conditional stimuli that signaled correct choices and across distance between the locations of the two choice keys. The standard deviation of time estimates (σ_s) increased linearly across time, with a slope of around 0.32, so time estimates became proportionally less precise with blackout duration (the scalar property; Gibbon, 1977). The standard deviation of location estimates (generically σ_L) fell hyperbolically across time, so location estimates became more precise with blackout duration. The model fitted the obtained data very well (Table 2; Figure 2) and either better or

as well as the model we used in Davison and Cowie (2022). Thus, the model’s approach clearly generalizes from concurrent-schedule procedures to a conditional-discrimination procedure. The results also validated a more theoretically consistent way of dealing with the effects of response-reinforcer control by assuming a generalization of control between response locations across a continuous dimension rather than the Davison and Nevin (1999) simple, categorical, confusion multiplier m .

Two of our results require further discussion. The first concerns the parameters of the model. We found here that the standard deviation of temporal discrimination, σ_s , increased linearly with blackout duration, which is inconsistent with Davison and Cowie’s (2022) finding that it increased ogivally. A linear increase is consistent with scalar timing (Gibbon, 1977); an ogival increase is not. An ogival function is also illogical in that it indicates that timing estimates have a constant standard deviation beyond a certain time. Davison and Cowie (2022) also reported evidence that location discrimination became worse according to an ogival function with increasing time, whereas the present experiment found the opposite. The standard deviation of location, σ_L , became smaller (reflecting more accurate discrimination) with increasing blackout duration. The simplest possibility for this disagreement is that the

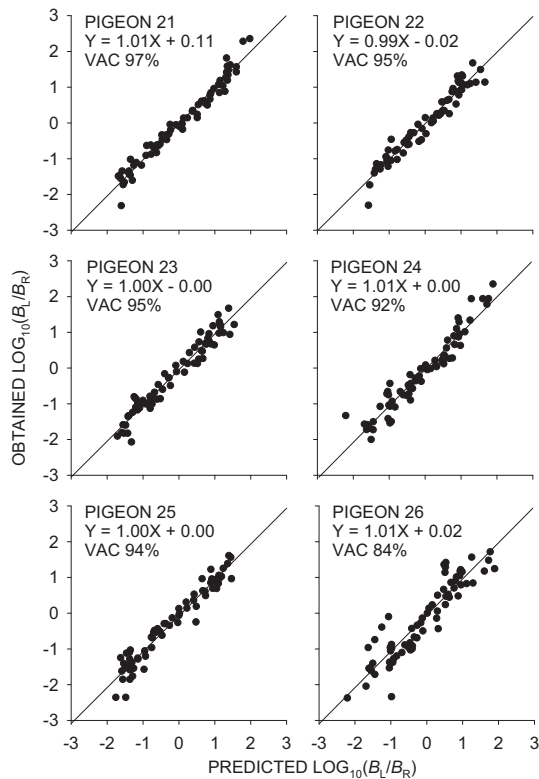


FIGURE 2 Obtained log response ratios as a function of log response ratios predicted from fitting Equation 4. The solid lines show the least-squares linear equation between obtained $\log(B_L/B_R)$ response ratios and the ratios predicted from fits to Equation 4. The equation of this regression and the percentage of variance accounted for by the regression is shown for each pigeon. The parameters of the fits are shown in Table 2.

procedure difference (concurrent scheduling versus conditional discrimination) caused this difference in results. A better possibility, which removes the odd nonlinear change in σ_s (which Davison and Cowie called s), is that the way that Davison and Cowie operationalized location generalization as m (as proportions rather than continuous redistribution functions; Equation 3) caused the difference in results. Further research should clarify which of these two possibilities is correct.

The second result that calls for further explanation is the need, in the present experiment, to allow a different $\log c$ for each condition in Equation 4. This was clearly demonstrated in the model analyses (Table 2) and has not been found (or at least reported) previously. Why did it occur? Figure 3 shows $\log c$ values across conditions as well as the key location that was correct for the set of shorter blackouts. Because the dependent variable was $\log_{10}(\text{Left/Right})$ responding, a positive $\log c$ indicated a bias to the Left key and a negative $\log c$ a bias to the Right key. As Figure 3 shows, the bias was generally toward the response reporting the set of longer (S2) durations. The average duration at which responding transitions to reporting S2 rather than S1 is the point of

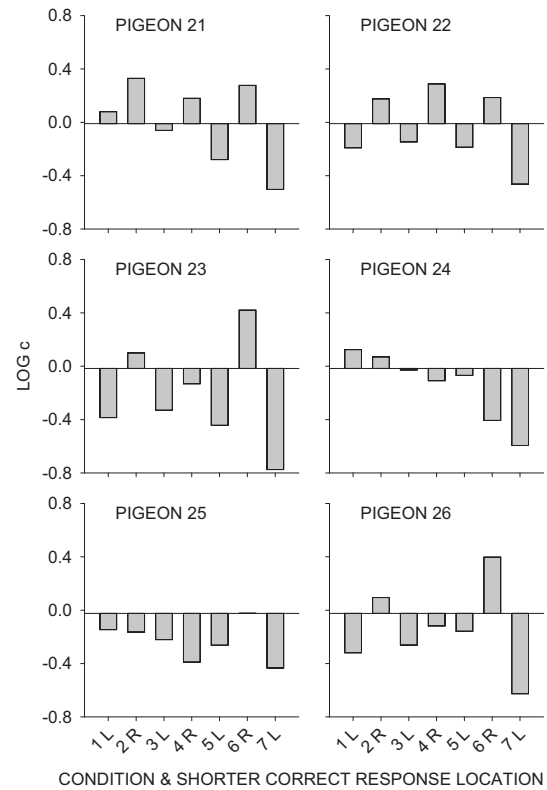


FIGURE 3 Measures of Left/Right response bias ($\log c$) obtained from the model fits. The x-axis also shows the condition and the choice key (Left or Right) that was correct for the shorter set (S1) of blackout durations.

subjective equality (PSE), which generally is closer to the geometric mean of a set of intervals (S1 and S2) rather than the arithmetic mean (Gibbon, 1981; Killeen & Fetterman, 1988). Thus, we estimated the PSE values for each pigeon and condition by fitting a general rational four-parameter ogive to the individual-pigeon log response-ratio data:

$$Y = Y_o + \frac{d}{1 + \left(\frac{e^{-1(X_i - X_o)}}{b} \right)}, \quad (5)$$

where Y is the log response ratio, d is the blackout duration, Y_o is the starting value of Y at $d = 0$, and X_o is the duration at which Y is halfway between the upper and lower bounds of the ogive. Fitting of the ogives was done using the Excel evolutionary solver, and we solved these ogives for the value of X at $Y = 0$ using the Excel GRG nonlinear solver. We stress that this function was not intended as a model of behavior but rather a generic *description* of behavior (as reported by Cowie et al., 2016a, 2016b) from which PSE values could be obtained.

The fitted ogives for the group data are shown in Figure 1, and Appendix A shows the ogive fits for each individual pigeon and condition. This rational function

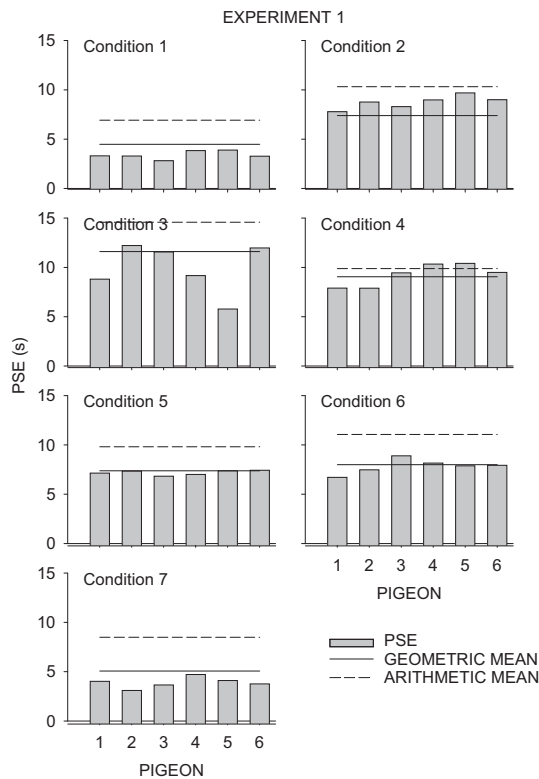


FIGURE 4 Estimates of points of subjective equality (PSE) for each pigeon and condition (see Appendix Figures A1–A7). The solid horizontal lines represent the geometric mean, and the dashed line is the arithmetic mean of the 10 arranged blackout durations.

fitted the data very well (on average, 98% variance was accounted for across all individual pigeons and conditions). The estimated PSEs for each pigeon and condition are shown in Figure 4 and were reasonably consistent across pigeons within each condition but showed rather more variation in Condition 3 than in the other conditions. In all conditions, the obtained PSE values were below, sometimes substantially, the mean of the 10 S1 and S2 intervals, thus biasing responding toward reporting the longer S2 set as we found. The PSE values were closer to the geometric mean of the set of S1 and S2 durations, though the geometric mean clearly overestimated the PSEs in Conditions 1 and 7 and underestimated them in Condition 2. The fact that the PSE values were less than the arithmetic mean of the S1 and S2 blackout intervals and closer to the geometric mean of these intervals indicates that the pigeons changed from reporting the smaller blackout duration set to reporting the longer blackout-duration set early in timing the blackouts. Because the blackout durations were equally likely and there was error in the estimation of duration (increasing σ_s with duration), this leads to a bias toward reporting the longer blackout-duration set. The size of the bias will, of course, depend on the way the S1 and S2 intervals are distributed in time and on the standard deviation σ_s of the component intervals.

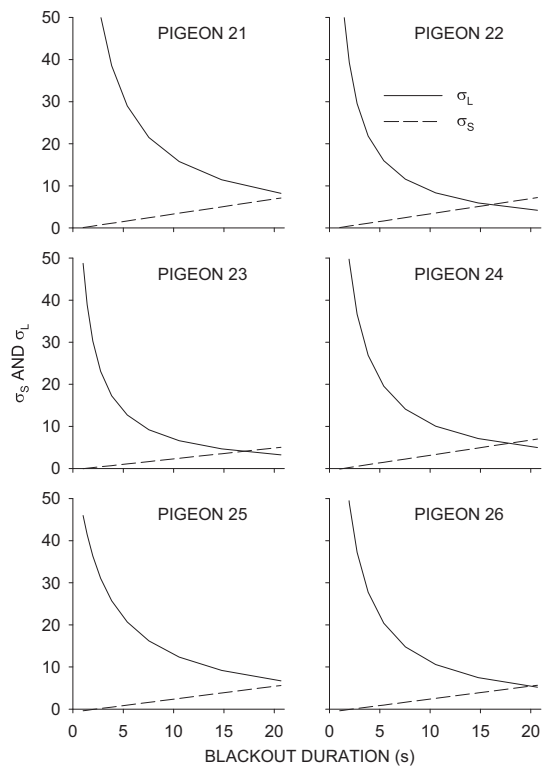


FIGURE 5 Changes in standard deviations σ_s and σ_L across blackout durations predicted by the fitted model for each pigeon.

More generally, the increasing σ_s and the decreasing σ_L across blackout duration suggests a consistency with another area of research, divided stimulus control (Davison, 2018; Davison & Elliffe, 2010; Shahan & Podlesnik, 2006, 2007). In divided stimulus control, using two stimulus dimensions, there is an inverse relation between control by one dimension and control by the other. Figure 5 shows the way in which the σ_s and σ_L components of the model are theoretically predicted to change across blackout duration based on the individual parameters from the model fits for each pigeon (Table 2). This figure shows a similar inverse relation for individual pigeons in the present results. In closely related research, Davison and McCarthy (1987) examined sensitivity and bias according to the Davison and Tustin (1978) model in the discrimination of a single duration from a set of variable durations. Their Figure 6 and Table 2 also show that sensitivity to reinforcement increased (i.e., σ_L decreased) when discriminability decreased (i.e., σ_s increased). Whether the inverse relation between σ_s and σ_L is a causal or correlational relation in the present data is unclear at present.

EXPERIMENT 2

Experiment 2 was designed to test the generality of the model structure and parameter values obtained in Experiment 1 in a simpler experimental arrangement using the

same pigeons and arranging just two blackout durations in each condition rather than two groups of five durations and measuring choice between these. The procedure was thus a standard conditional-discrimination procedure. One of the blackout durations intermittently provided reinforcers for correct left-key responses, and the other provided reinforcers for correct right-key responses.

Method

Subjects and Apparatus

The same pigeons and equipment were used in [Experiment 2](#). Pigeons 24 and 25 died during [Experiment 2](#), and their partial data were not used in the analyses.

Procedure

[Experiment 2](#) used the same base procedure as [Experiment 1](#), but S1 and S2 were each single blackout durations rather than two sets of blackout durations. The blackout durations in [Experiment 2](#) and the time between the two durations were varied across 10 conditions (Table 3). We numbered these Conditions 8 through 17, continuing from [Experiment 1](#). Condition 8 commenced immediately after Condition 7 of [Experiment 1](#). Apart from Conditions 8 and 9, there were two main manipulations: first, keeping the shorter blackout at 2.5 s and varying the other (Conditions 10 to 13) and, second, keeping the longer blackout at 30 s and varying the shorter (Conditions 13 to 17).

Results and Discussion

Figure 6 shows the log response ratios averaged across the four pigeons as a function of log response ratios

TABLE 3 Blackout durations arranged in [Experiment 2](#).

Condition	BO1 (s) LC	BO2 (s) RC	Sessions
8	15.0	5.0	98
9	7.5	12.5	94
10	2.5	17.5	45
11	12.5	2.5	67
12	2.5	7.5	60
13	30.0	2.5	88
14	17.5	30.0	82
15	30.0	5.0	56
16	30.0	12.5	56
17	30.0	25.0	78

Note: Two blackout intervals (BO1 and BO2) were arranged, and LC and RC are the locations of correct responses following each blackout duration.

predicted using the model parameters for grouped data obtained from our model of the [Experiment 1](#) data. Appendix [Figure B1](#) shows the log response ratios in the presence of S1 and S2 in [Experiment 2](#) for data from each condition and pigeon. The four pigeons showed very similar changes between the two stimuli in each condition, apart from Pigeon 21 in Condition 9. As [Figure 6](#) implies, for some conditions the [Experiment 1](#) parameters yielded predicted log response ratios that were close to those obtained but in many others the predictions were poor, particularly when the S1 and S2 blackout durations were more different. In these conditions, the [Experiment 1](#) parameters typically predicted less discrimination between the durations than was obtained.

[Figure 7](#) shows the obtained log response ratios for each pigeon plotted as a function of predicted log response ratios using each pigeon's [Experiment 1](#) parameters, excluding log *c*: no log *c* values can be unambiguously predicted for the [Experiment 2](#) blackout durations from [Experiment 1](#). [Figure 7](#) also shows the predicted-obtained regression lines and equations thereof. Although the predicted-obtained slopes were reasonably close to 1.0 and the intercepts reasonably close to 0 (i.e., perfect overall prediction), the obtained data deviated considerably and systematically from predictions. The variances accounted for by the fitted lines were 76, 78, 66, and 64%, respectively, across the four pigeons, which is poor for such choice data. We cannot take this as a satisfactory prediction of the [Experiment 2](#) data from the

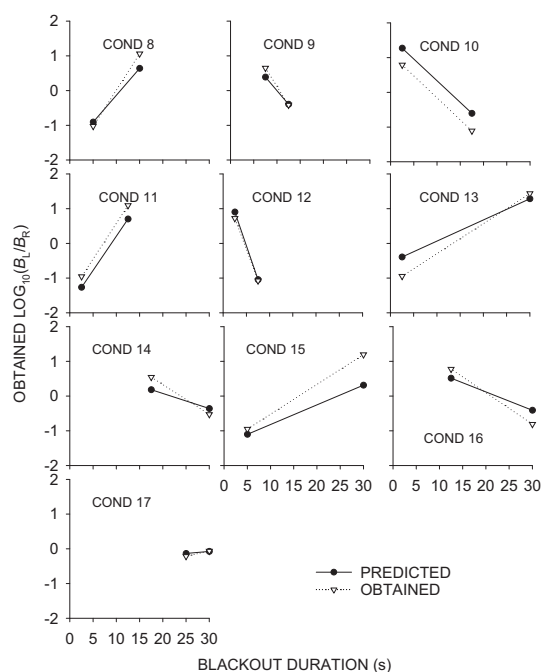


FIGURE 6 Average obtained log response ratios and log response ratios predicted from Equation 4 using the fitted parameters from [Experiment 1](#) for each condition of [Experiment 2](#). Appendix [Figure B1](#) shows the data for each pigeon.

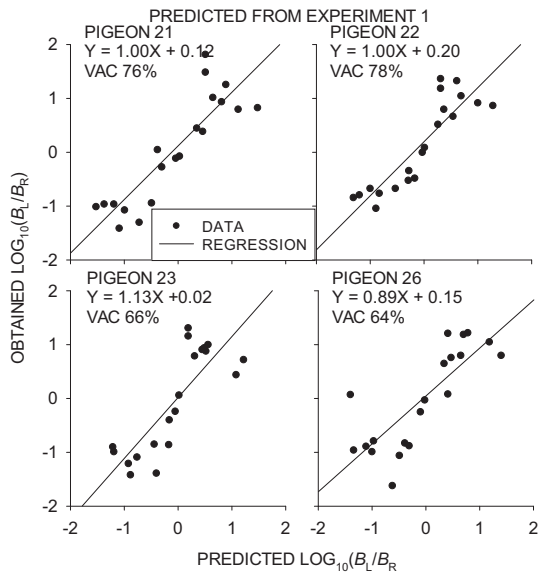


FIGURE 7 Obtained log Left/Right response ratios as a function of log ratios predicted from the parameters of the fits to Experiment 1 for individual pigeons. The solid lines show the least-squares linear equation between the predicted and obtained data. The equation of this regression and the percentage of variance accounted for by the regression is shown for each pigeon.

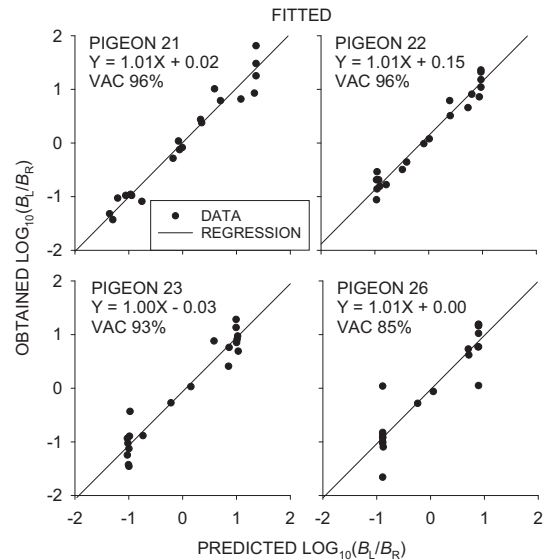


FIGURE 8 Obtained log response ratios as a function of predicted log response ratios from Equation 4 fits to the results of Experiment 2. The solid lines show the least-squares linear equation between the predicted and obtained data. The equation of this regression and the percentage of variance accounted for by the regression is shown for each pigeon.

TABLE 4 Parameters obtained by fitting the model to individual-pigeon data in Experiment 2.

	Pigeon21	Pigeon22	Pigeon23	Pigeon26
σ_L (k)	18.36	7.40	8.61	9.39
σ_L (h)	>1E3	>1E3	309.03	>1E3
σ_S (I)	0.17	0.00	1.14	0.00
σ_S (S)	0.51	0.36	0.14	0.24
VAC	0.96	0.93	0.93	0.95

Note: σ_L (h) was limited to 1E3.

Experiment 1 parameters. Because we constrained log c as zero in our predictions, at least some of these predicted–obtained deviations might be consistent with a nonzero log c . Such an omission would provide predictions that were displaced from but parallel to the data; although this is evident in Conditions 10 and 11, it did not generally occur, suggesting that systematic changes in log c were not the source of the errors in the predictions.

These poor predictions do not necessarily mean that the model that was effective in Experiment 1 is not applicable to the choice between just two delays; perhaps the model can accommodate the Experiment 2 data but with parameters different from those in Experiment 1? Thus, we carried out fits of the model used in Experiment 1 (Equation 4) to the Experiment 2 data. The fits used 10 data from each pigeon with four free parameters (Table 4) and were carried out in the same manner as in Experiment 1. The results are shown in Figure 8 and

Table 4. The predictions matched the data much better in terms of variance accounted for—an average of 95% when directly fitted compared with an average 74% when predicted from Experiment 1 parameters (compare Figures 7 and 8). The slopes of the regression between data and prediction were very close to 1.0, and the intercepts were close to 0 apart for Pigeon 22. Thus, the model provided an excellent account of data from Experiment 2.

Comparing the obtained parameter values in Tables 2 and 4, it is clear why the predictions using Experiment 1 parameters failed accurately to predict the Experiment 2 data: in Experiment 1, the estimates of σ_L (h) were very high, so the location distribution σ_L itself remained constant at σ_L (k) across conditions in Experiment 2. In fitting the model to the Experiment 2 data, we limited the value of the half-life of the hyperbolic decrease (σ_L (h); Table 2) to 1,000.² Although the value of σ_L (h) for Pigeon 23, a half-life of 309 s, differed from the values of > 1E3 for the other three pigeons, the obtained σ_L changed very little across the blackout durations used in Experiment 2—from 8.5 at 2.5 s to 7.9 at 30 s. We conclude that σ_L was constant in Experiment 2 at the values given by σ_L (k) and thus unaffected by blackout delays. The change in the temporal-generalization parameter σ_S across blackouts was reasonably similar to those found in Experiment 1 (Table 2), averaging 0.31 for these pigeons in both Experiments 1 and 2.

²The values of the half-lives in the Experiment 1 modeling were less than 1,000.

GENERAL DISCUSSION

The extent to which behavior comes under control by a contingency depends critically on both stimulus and reinforcer control. The general approach to understanding such combined control by time and location that we have espoused (Cowie & Davison, 2020, 2022; Davison & Cowie, 2022), with a minor modification for intramodel consistency, did a good job of describing changes in response locations across sets of blackout durations when correct responding was conditionally signaled by two sets of durations (Experiment 1). The model parameters obtained in Experiment 1 failed accurately to predict choice when the conditional stimuli were just two blackout durations (Experiment 2). However, the *approach* used to model Experiment 1 data described Experiment 2 data very well when it was directly fitted to the data, albeit by assuming that σ_L was constant across blackout duration (that is, with only three free parameters). Thus, the σ_S - σ_L model accommodates the data from both Experiments 1 and 2, but the way in which it accommodated generalization across the location dimension was different.

If there is a problem with our model (Equation 4) it is that fitting required a different value of $\log c$ for each experimental condition in Experiment 1. Without this requirement, and assuming a constant $\log c$ across conditions, it would have required five free parameters for 70 data points, but we had to use 11 free parameters. Although the ratio of data to number of free parameters was better than in many model fits in choice research, the sheer number of free parameters may cause consternation. But the condition-dependent free $\log c$ parameters do point to a fundamental finding that needs further research for full understanding. Although it would be easy to hide this problem by subtracting the overall (S1 and S2) $\log_{10}(B_I/B_R)$ values from those following each blackout duration, the model would then only account for the transformed behavior, not the raw behavior itself.

When the task was to discriminate between two five-item sets of blackout durations, σ_L decreased hyperbolically across the constituent blackout durations, but when the task was to discriminate between just two blackout durations, σ_L remained constant across the durations arranged. The second of these results is more understandable because the correct-response locations remained unchanged across blackout durations and we would expect no interaction between blackout duration and location discrimination, though there seem to be no direct experimental results that have previously shown this. It is the result from Experiment 1 in which σ_L decreased hyperbolically in relation to blackout duration (and the similar changes we have previously reported from when concurrent VI schedules reversed reinforcer ratios at fixed times since the previous reinforcer; Davison & Cowie, 2022; Cowie & Davison, 2020) that is unexpected and indeed hard to explain. Does this result arise, then, from the inherent variability in the stimuli in Experiment 1, as distinct from fixed

durations signaling different contingencies of reinforcement in Experiment 2? Further research will address this possibility.

The contrary directional changes in σ_S and σ_L across blackout duration in Experiment 1 across time (Figure 5) are consistent with findings from the study of divided stimulus control: when two sources of control are compounded, increasing control by one source decreases control by the other (Davison, 2018; Davison & Elliffe, 2010; Shahan & Podlesnik, 2006, 2007). But as this relation was absent in Experiment 2, it is not a tenable explanation for the Experiment 1 results.

An additional finding that requires explanation is the need for different $\log c$ values in Experiment 1. These inherent bias values should have remained constant (as they did in Experiment 2) because the characteristics of the choice keys remained constant across conditions, but assuming a constant bias value produced poor model fits. It is entirely conceivable that the condition-specific $\log c$ values are related to the above finding that σ_L decreased with blackout-duration because $\log c$ variation was not required for the model fit in Experiment 2 when σ_L was found to be constant. According to the model, larger σ_L distributions disperse obtained reinforcers more widely across location, whereas smaller σ_L distributions focus obtained reinforcers more closely on the reinforced response location. Such a differential focus will bias choice to the location that is correct for longer durations, which is the pattern displayed in Figure 3. The lack of change of σ_L across blackout duration in Experiment 2 removed the $\log c$ bias. If increasing temporal variance changes the relation between σ_L and blackout duration, this increase will also increase bias toward the response that is correct for longer blackouts. This finding underlines the need to investigate the relation between variance in conditional temporal-discrimination tasks—and maybe tasks that assess discrimination across other dimensions—and choice in future research. Possibly germane here is the finding (Davison, 1972) that choice between fixed-interval and mixed-interval schedules with the same mean interval increased as the number of intervals in the mixed schedule was increased. Thus, it might be informative to investigate an arrangement that combines the present Experiments 1 and 2 with S1, a single fixed duration, and S2, a set of variable durations.

The model we propose here is a model that combines temporal distance with orthogonal reinforcer location. Although it is a model of dimensional control, any such model needs to understand stimulus control more generally. Thus, it may also be useful to measure stimulus control when conditional stimuli vary on more than a single dimension, as did Blough (1972). Equally, we might ask how the model could deal with two correlated, rather than orthogonal, dimensions such as when the correct-choice location progressively becomes more distant with elapsed time. Additionally, if the model understands variations in physical distance (rather than just a single physical distance as in the present experiments) equally well as

it does variations in temporal distance, it should be possible to determine whether physical distance also has similar scalar properties to temporal distance.

The current model is viable but probably incomplete. In the way we instantiated it here, it has the benefit of displaying our assumption that all dimensional controlling stimulus variables, be they elapsed times, conditional times, physical distances, and even dimensional response differences (Davison et al., 2020), may be dealt with as modulating reinforcer values in the same way—by Gaussian generalization across the dimensions. This approach appears to work well whether the temporal stimulus is a time from a marker event (Davison & Cowie, 2022) or is a conditional stimulus in a conditional-discrimination procedure. Being able to combine multidimensional stimulus and reinforcer control in this way is a major development in the prediction of behavior—specifically of choice because, as Herrnstein (1970) rightly stated, all behavior is choice behavior.

AUTHOR CONTRIBUTIONS

MD and SC made equal contributions in all aspects of experiment planning, data collection, data analysis, and manuscript writing.

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CONFLICT OF INTEREST STATEMENT

The authors have no conflicts of interest.

DATA AVAILABILITY STATEMENT

The raw data from the experiments reported here are available at <https://doi.org/10.17605/OSF.IO/NW68Y>.

ETHICS APPROVAL

This research was carried out under the University of Auckland Ethical Approval AEC2657.

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APPENDIX A

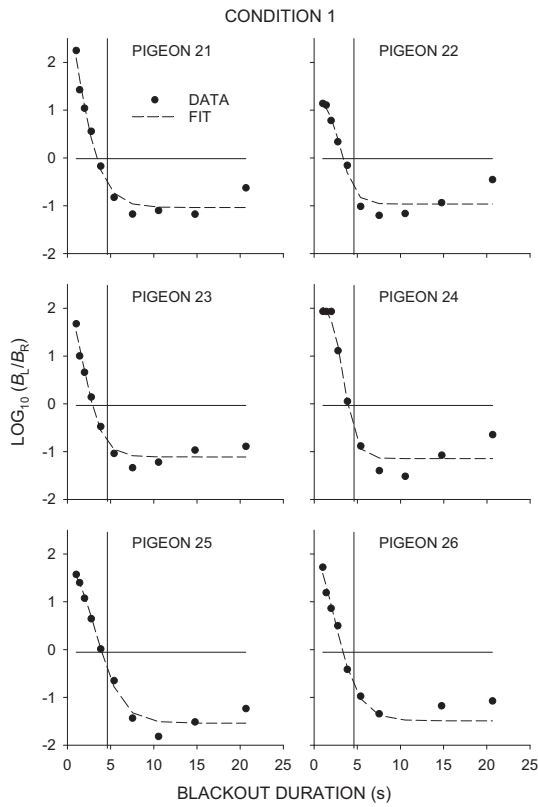


FIGURE A1 Log response ratios as a function of blackout duration, and the fit of the generic four-parameter ogival curve (Equation 5) for each pigeon in Condition 1. The horizontal line denotes zero log response ratio (equal choice), and the vertical line shows the geometric mean of the 10 blackout intervals comprising S1 and S2.

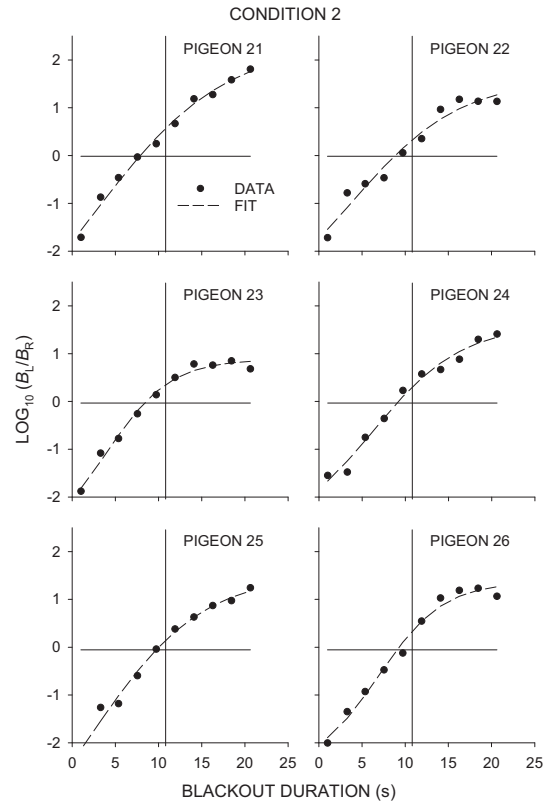


FIGURE A2 Log response ratios as a function of blackout duration, and the fit of the generic four-parameter ogival curve (Equation 5) for each pigeon in Condition 2. The horizontal line denotes zero log response ratio (equal choice), and the vertical line shows the geometric mean of the 10 blackout intervals comprising S1 and S2. One data point fell off the graph for Pigeon 25.

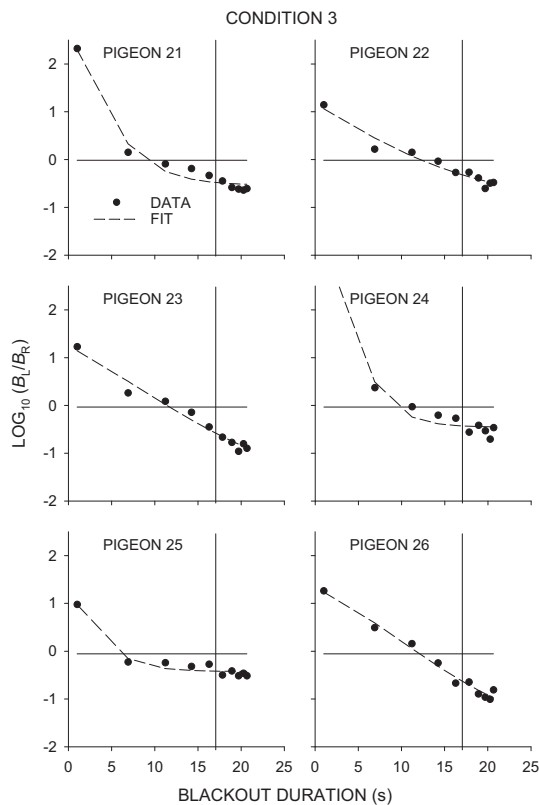


FIGURE A3 Log response ratios as a function of blackout duration, and the fit of the generic four-parameter ogival curve (Equation 5) for each pigeon in Condition 3. The horizontal line denotes zero log response ratio (equal choice), and the vertical line shows the geometric mean of the 10 blackout intervals comprising S1 and S2. One data point fell off the graph for Pigeon 24.

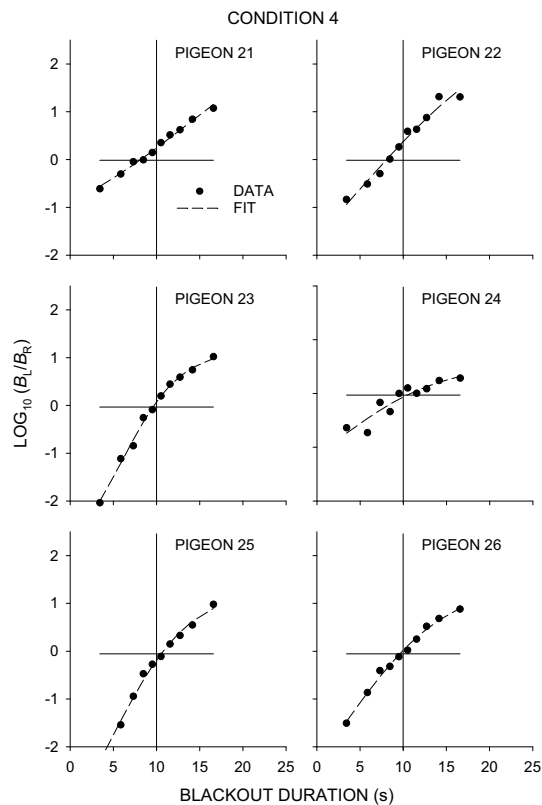


FIGURE A4 Log response ratios as a function of blackout duration, and the fit of the generic four-parameter ogival curve (Equation 5) for each pigeon in Condition 4. The horizontal line denotes zero log response ratio (equal choice), and the vertical line shows the geometric mean of the 10 blackout intervals comprising S1 and S2. One data point fell off the graph for Pigeon 25.

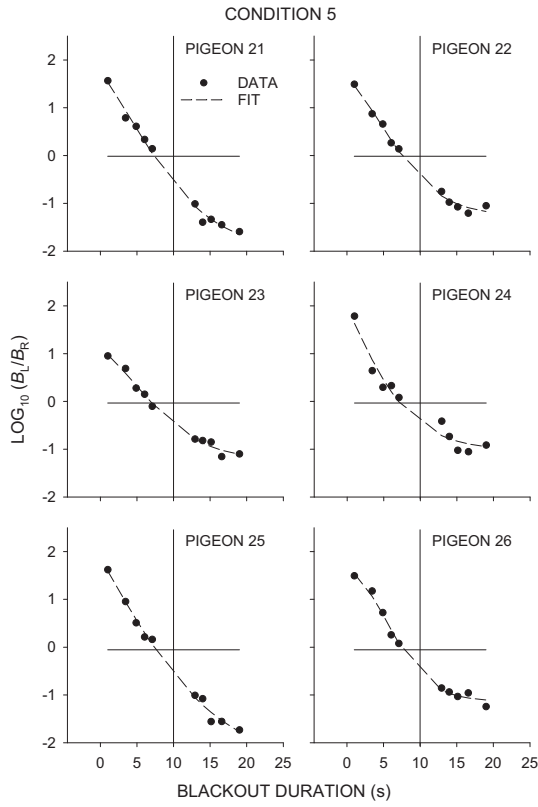


FIGURE A5 Log response ratios as a function of blackout duration, and the fit of the generic four-parameter ogival curve (Equation 5) for each pigeon in Condition 5. The horizontal line denotes zero log response ratio (equal choice), and the vertical line shows the geometric mean of the 10 blackout intervals comprising S1 and S2.

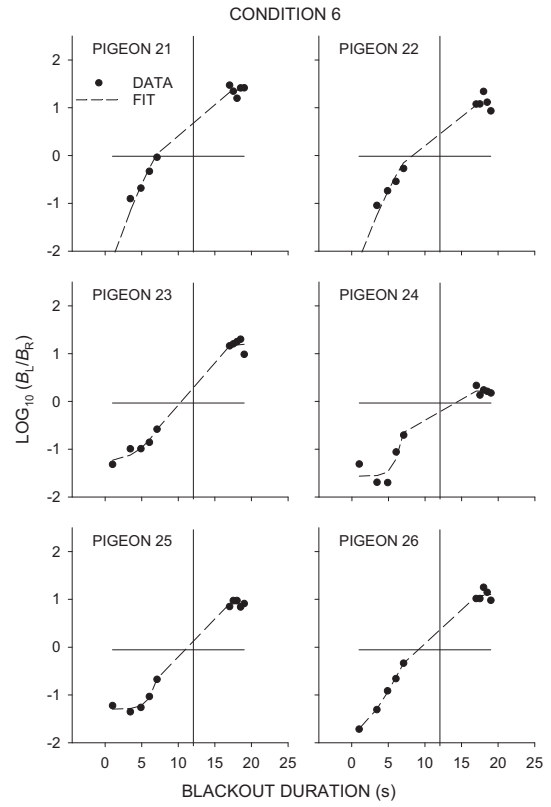


FIGURE A6 Log response ratios as a function of blackout duration, and the fit of the generic four-parameter ogival curve (Equation 5) for each pigeon in Condition 6. The horizontal line denotes zero log response ratio (equal choice), and the vertical line shows the geometric mean of the 10 blackout intervals comprising S1 and S2. Data points fell off the graph for Pigeons 21 and 22.

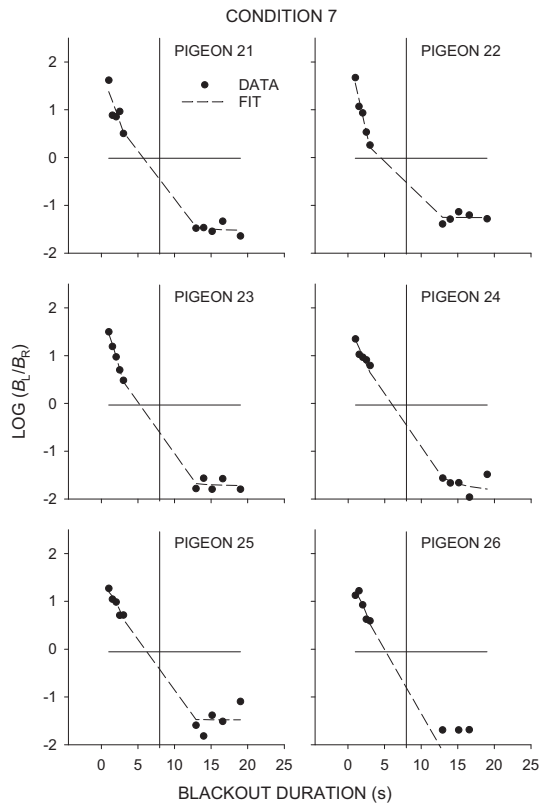


FIGURE A7 Log response ratios as a function of blackout duration, and the fit of the generic four-parameter ogival curve (Equation 5) for each pigeon in Condition 7. The horizontal line denotes zero log response ratio (equal choice), and the vertical line shows the geometric mean of the 10 blackout intervals comprising S1 and S2. One point fell off the graph for Pigeon 26.

APPENDIX B

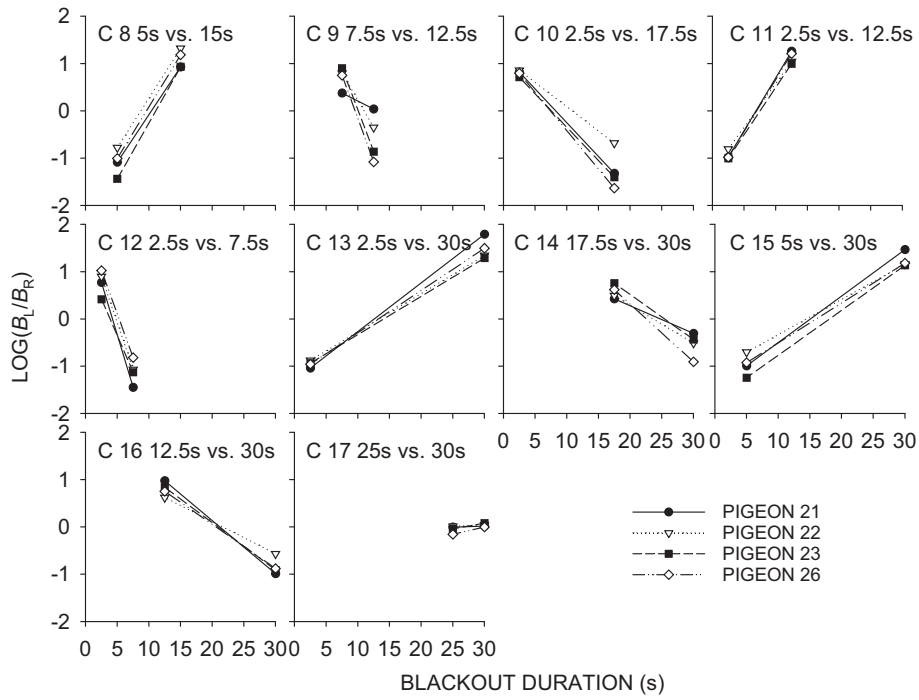


FIGURE B1 Log response ratios as a function of blackout duration for each pigeon in each in each condition in Experiment 2. C denotes condition.