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Further Tests of a Two-State Model for Choice Reaction Times

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Falmagne proposed that choice reaction times can be described by a simple model involving two states of perceptual-motor preparation. Lupker and Theios found support for the model in an n-choice ($n = 4$, 6) reaction time task in which stimulus presentation probability was varied as π for one stimulus, but was constrained as $(1 - \pi)/(n - 1)$ for all the remaining stimuli. The present experiments involve four- and six-choice tasks in which the stimuli differ in their individual presentation probabilities. Sequential mean reaction times and various properties of the reaction time distributions are considered. The model was able to predict with reasonable accuracy all the sequential mean reaction times except those for alternating stimulus sequences. The fixed point and other distributional properties seemed to hold on a general level. However, detailed inspection revealed a few systematic deviations between the data and distributional properties predicted by the two-state model.

Falmagne (1965) has proposed a simple, binary mixture model for choice reaction time which can be completely specified by three assumptions.

1. On any trial the subject is either prepared or unprepared for each possible stimulus.

2. If the subject is prepared for the presented stimulus on a trial, his reaction time is a random sample from a distribution, $f_1(t)$, with mean μ_1 and variance σ_1^2. If the subject is unprepared for the presented stimulus on a trial, his reaction time is a random sample from a distribution, $f_2(t)$, having mean μ_2 and variance σ_2^2 where $\mu_1 < \mu_2$ and $\sigma_1^2 \leq \sigma_2^2$.

3. A subject changes his state of preparation for a stimulus in the following manner: If he was prepared for a stimulus on Trial n and that stimulus was presented on Trial n, he maintains his preparation for that stimulus. If the stimulus was not presented, he loses his preparation with probability a. If he was unprepared for a stimulus and it was presented, he becomes prepared for it on Trial $n + 1$ with probability a'. If the stimulus was not presented on Trial n, he remains unprepared for it on Trial $n + 1$.

From these three assumptions, Falmagne derived p_i, the asymptotic probability of being prepared for Stimulus i,

$$p_i = \pi_i a/[\pi_i a + (1 - \pi_i)a'], \qquad (1)$$

where π_i is the presentation probability of Stimulus i. The reader should note that if it is assumed that $a = a'$, the probability of being prepared for Stimulus i reduces to π_i. It should also be noted that p_i is always a monotonic function of π_i.

Falmagne's (1965) model yielded a good fit to his own data (i.e., mean reaction times, repetition reaction times, and empirical variances) in a six-choice reaction time task. However, Falmagne (1968) later demonstrated that his empirical reaction time distributions failed to satisfy a simple property of binary mixture models. This property, called the *fixed point property*,

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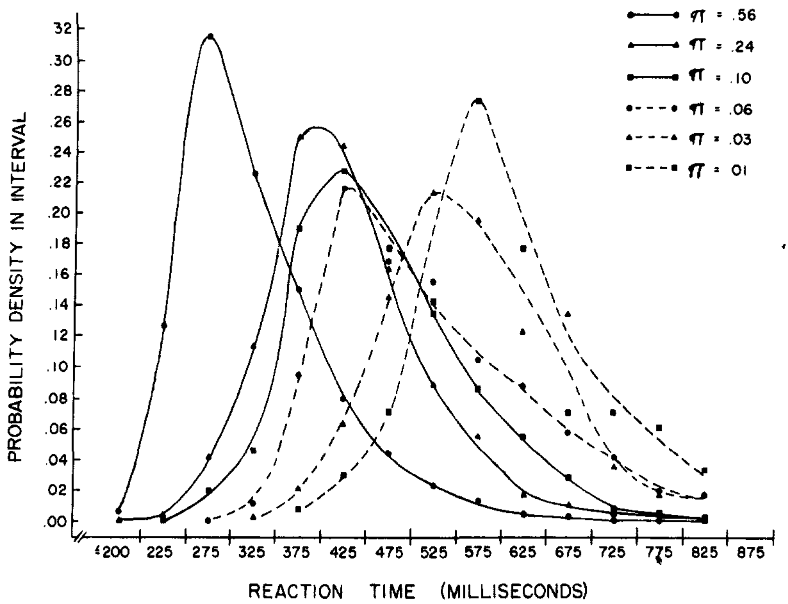

Figure 1. Obtained probability density functions from Falmagne's (1965) six-choice reaction time task.

can be demonstrated quite simply by considering the fact that we can write the empirical density function for Stimulus i, $g_i(t)$, as a combination of the two theoretical density functions, $f_1(t)$ and $f_2(t)$:

$$g_i(t) = p_i \cdot f_1(t) + (1 - p_i) \cdot f_2(t), \quad (2)$$

where again p_i is the asymptotic probability of being prepared for Stimulus i. Because of the nature of continuous density functions, there must exist a point, t_o, at which $f_1(t_o) = f_2(t_o) = c$. That is, there must exist a point at which the two theoretical density functions cross. Therefore, by examining Equation 2, we can see that the empirical density functions at t_o, (i.e., $g_i(t_o)$) take on the same value, c, for all stimuli. That is,

$$g_i(t_o) = p_i \cdot f_1(t_o) + (1 - p_i) \cdot f_2(t_o),$$

is equivalent to

$$g_i(t_o) = p_i \cdot c + (1 - p_i) \cdot c,$$

which implies

$$g_i(t_o) = (p_i + 1 - p_i) \cdot c = c.$$

Falmagne's (1968) empirical distributions, however, as displayed in Figure 1 did not exhibit a fixed point.

More recently, Theios and Smith (1972) have demonstrated good support for Falmagne's model in a two-choice reaction time task and Lupker and Theios (1975), working with the assumption that $a = a'$, have demonstrated that the model can give a good account of the data (mean reaction times, sequential reaction times, as well as the fixed point property) in four- and six-choice reaction time tasks. Lupker and Theios suggested the apparent contradiction between their findings and those of Falmagne (1968) arose because three of Falmagne's stimuli were presented so infrequently (presentation probabilities of .06, .03, and .01) that the subject essentially "forgot" about them. Therefore, on the few trials when they were presented, the subject was in a deep state of unpreparedness, so that a third distribution came into play. This idea is supported rather well by Falmagne and Theios (1969), who found that a three state preparation model gave a good account of Falmagne's original data.

Posner (Note 1) suggested, however, that because of the way Lupker and Theios (1975) selected the presentation probabilities, the subjects were essentially forced into dichotomizing the stimulus set, thus yielding results that can be interpreted in terms of a binary mixture. In both of Lupker and Theios' experiments, one stimulus was presented with an arbitrary preselected probability, π, while the other $n - 1$ stimuli were all presented with probability $(1 - \pi)/(n - 1)$. It had been necessary for Lupker and Theios to do this in order to obtain predictions from one of the reaction time models they tested. The point of the present experiment is to test whether Lupker and Theios' results can be replicated in four- and six-choice tasks when the stimuli all have different presentation probabilities, which are at least as large as .10.

In addition to looking at the same aspects of the data as Lupker and Theios did, three other distributional properties of binary mixtures are considered. The first of these is a consequence of the fixed point property. Consider just two stimuli, i and j, where $\pi_i > \pi_j$ and, therefore, $p_i > p_j$. We can write the difference between their density functions $g_i(t) - g_j(t)$ as the following:

$$\begin{aligned} g_i(t) - g_j(t) &= p_i \cdot f_1(t) - p_j \cdot f_1(t) \\ &\quad + (1 - p_i) \cdot f_2(t) - (1 - p_j) \cdot f_2(t) \\ &= (p_i - p_j) \cdot [f_1(t) - f_2(t)]. \end{aligned}$$

For all $t < t_0$ (the fixed point), $f_1(t) > f_2(t)$ and therefore the difference $g_i(t) - g_j(t)$ should be positive. However for all $t > t_0$, $f_1(t)$ is now less than $f_2(t)$, so $g_i(t) - g_j(t)$ should be negative. In other words, for all $t < t_0$ the ordinal positions of the distributions must be maintained, but at t_0 this ordinal relationship should reverse itself. Noreen (Note 2) pointed out this property of binary mixtures to us.

The next two properties concern the cumulative distribution functions $G_i(t)$. The first of these is analogous to Sternberg's (Note 3) Long Reaction Time property. As with the density functions, we can write these as binary mixtures,

$$G_i(t) = p_i \cdot F_1(t) + (1 - p_i) \cdot F_2(t)$$
$$G_j(t) = p_j \cdot F_1(t) + (1 - p_j) \cdot F_2(t).$$

If we then consider the difference $G_i(t) - G_j(t)$, we can, as with the density functions, reduce it to the following:

$$G_i(t) - G_j(t) = (p_i - p_j) \cdot [F_1(t) - F_2(t)]. \quad (3)$$

By the nature of the two functions, $F_1(t)$ is greater than $F_2(t)$ for all values of t. If we let $\pi_i > \pi_j$ so that $p_i > p_j$, we can see that this difference should never be negative. Therefore, empirically $G_i(t)$ and $G_j(t)$ should never cross at any value of t.

For the final property (Link, Ascher, & Heath, Note 4), let us introduce a third distribution, $G_k(t)$, and consider another difference:

$$G_k(t) - G_j(t) = (p_k - p_j) \cdot [F_1(t) - F_2(t)]. \quad (4)$$

If we make a ratio of Equations 3 and 4, we can see that this ratio is predicted to be constant:

$$\frac{G_i(t) - G_j(t)}{G_k(t) - G_j(t)} = \frac{(p_i - p_j) \cdot [F_1(t) - F_2(t)]}{(p_k - p_j) \cdot [F_1(t) - F_2(t)]} = \frac{p_i - p_j}{p_k - p_j}.$$

Empirically, what this means is that at any value of t, this ratio of differences should be the same. In addition, if we assume that $a = a'$, we have parameter-free predictions of this ratio because p_i reduces to π_i, the stimulus presentation probability (see Equation 1).

Method

Subjects

The four- and six-choice tasks were run in the same experimental period. Thirty University of Wisconsin undegraduates (13 males and 17 females) took part. They all received course credit for their participation. All were right-handed. The first 24 took part in both tasks; the last 6 only took part in the six-choice task.

Apparatus

The subject was seated in an armchair that had four buttons mounted on the end of each arm under each of the subject's four fingers (excluding the thumb). The chair was enclosed in an Industrial Acoustic Co. (Model 410A) sound-attenuating room. The chair was positioned so that the subject could see the screen of a Tektronix (Type RM 503) oscilloscope which was placed against a 54 × 34.5 cm window in the booth. The remainder of the window was occluded. The stimuli were green digits 3, 4, 5, 6, 7, and 8 (approximately 1 cm tall) presented on the oscilloscope screen about .6 m from the subject. A Digital Equipment Corp. PDP-8 computer was programmed to present the stimuli and to record on magnetic tape the stimulus, the response, and the reaction time for each trial.

Procedure

In the four-choice task, the presentation probabilities selected were .40, .30, .20, and .10. In the six-choice task, the presentation probabilities were .30, .20, .15, .15, .10, and .10. To counterbalance properly, 24 probability–stimulus mappings were constructed for the four-choice task and 36 probability–stimulus mappings were constructed for the six-choice task. Each subject received four, 300-trial sessions with a 5-min. rest between sessions. The first 10 trials of each session were considered practice and were disregarded. One probability–stimulus mapping was used in the first two sessions; a different probability–stimulus mapping was used in the last two sessions. For the first 24 subjects, two of their sessions used one of the four-choice mappings; their other two sessions used one of the six-choice mappings. Of these subjects, 12 received the four-choice task first and 12 received the six-choice task first. The remaining 6 subjects received one of the six-choice probability–stimulus mappings in their first two sessions and another one in their last two sessions. Because of this procedure, every stimulus was assigned every probability equally often and, therefore, each stimulus occurred equally often over the course of the experiment.

A trial consisted of one of the stimuli being randomly selected according to the assigned probabilities and being presented to the subject. The response–stimulus interval was 500 msec; and, as stated, each subject received four, 300-trial sessions with a 5-min. rest between sessions. Any session with more than 5% errors was immediately rerun. The stimulus–response mapping was 3–left ring finger, 4–left middle finger, 5–left index finger, 6–right index finger, 7–right middle finger, and 8–right ring finger. Stimulus 3 and Stimulus 8 were, of course, not used in the four-choice task.

Results

Mean Reaction Times

To get predictions for mean reaction times and first- and second-order sequential reaction times for each stimulus presentation probability in both tasks, it was necessary to estimate five parameters. The assumptions made were (a) $a = a'$ is a constant for all stimuli in a task, (b) μ_1 does not vary over tasks, and (c) μ_2 for the six-choice task is larger than μ_2 for the four-choice task. Chandler's (1969) subroutine STEPIT was used to estimate μ_1, the two values of μ_2, and the two values of a. The values STEPIT yielded were $\mu_1 = 338$, $\mu_2 = 600$ (four choice), $\mu_2 = 669$ (six choice), $a = .30$ (four choice), and $a = .35$ (six choice). The fit of the two-state model to the data can be seen in Tables 1 and 2 which contain the mean and sequential reaction times for all four presentation probabilities for both tasks. The sequences should be read left to right, a 0 indicating that the stimulus under consideration was not presented on that trial and a 1 indicating that the stimulus

Table 1
Obtained and Predicted Sequential Mean Reaction Times (in msec) for All Four Presentation Probabilities for the Four-Choice Task

	$\pi_i = .10$		$\pi_i = .20$		$\pi_i = .30$		$\pi_i = .40$	
Sequence[a]	Obtained	Predicted	Obtained	Predicted	Obtained	Predicted	Obtained	Predicted
(mean) 1	576	574	543	548	520	521	495	495
11	494	504	480	486	474	467	458	449
01	587	582	557	563	539	545	521	526
111	421	455	411	442	440	429	430	416
011	503	510	500	497	490	484	478	471
101	616	533	558	519	544	506	515	593
001	584	587	557	574	536	561	524	548

[a] 1 = stimulus presented; 0 = stimulus not presented.

Table 2
Obtained and Predicted Sequential Mean Reaction Times (in msec) for All Four Presentation Probabilities for the Six-Choice Task

	π_i = .10		π_i = .15		π_i = .20		π_i = .30	
Sequence[a]	Obtained	Predicted	Obtained	Predicted	Obtained	Predicted	Obtained	Predicted
(mean) 1	638	636	618	619	604	603	572	570
11	522	532	511	521	501	510	493	489
01	649	647	638	637	628	626	608	604
111	449	464	471	457	464	450	461	436
011	528	539	517	532	509	525	506	511
101	647	580	630	573	618	566	589	552
001	649	655	639	648	631	641	615	627

[a] 1 = stimulus presented; 0 = stimulus not presented.

under consideration was presented on that trial. The reaction time under consideration is from the trial signified by the 1 which is always in the rightmost position of any sequence.

A chi-square test developed by Falmagne, Cohen, and Dwivedi (1975) was performed on the 56 predictions (seven sequences, four different probabilities, two different tasks). This analysis, based on 51 degrees of freedom, yielded a chi-square of 198.34, which casts some degree of doubt on the validity of the model. However, a closer look at this analysis reveals that the eight 101 (alternation) sequences accounted for most (136.3) of this chi-square value. In general, the model adequately predicts the other 48 data points, especially the mean and first-order sequential reaction times. However, it consistently underpredicts the reaction time to the alternation sequence, which is often no different from the reaction time to the double nonrepetition sequence (i.e., 001). It should be pointed out that the chi-square on the remaining 48 data points (62.04) is barely significant ($.05 > p > .025$) on $48 - 5 = 43$ degrees of freedom. However, this analysis suffers from the fact that the parameter values used were chosen to fit all 56 points, not just these 48.

Distributional Properties

The graphs of the empirical density functions can be found in Figures 2 and 3 for the four- and six-choice tasks, respectively.

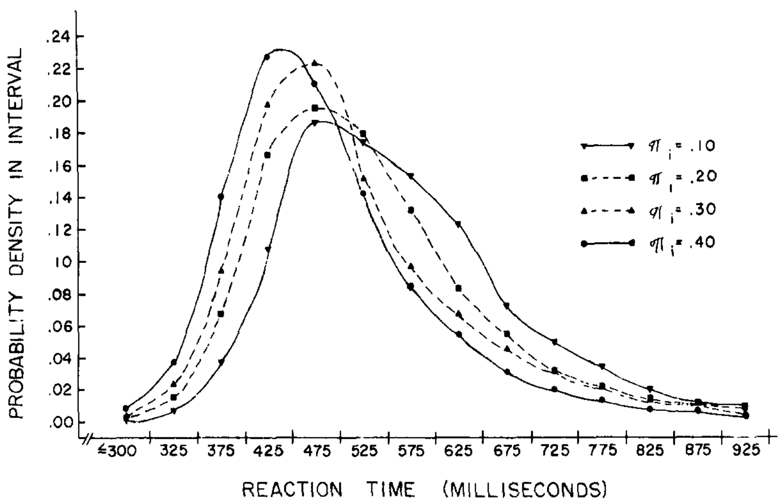

Figure 2. Obtained probability density functions for the four-choice reaction time task (Note the approximately equal probability density for all the functions in the neighborhood of 500 msec).

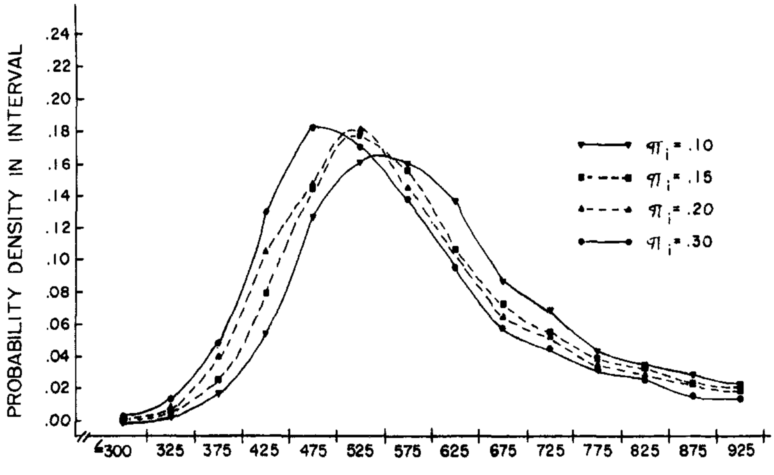

Figure 3. Obtained probability density functions for the six-choice reaction time task (Note the approximately equal probability density in the neighborhood of 550 msec).

The reader is left to judge for himself the adequacy of the fit of the fixed point property. We suggest, however, that there seems to be a fixed point around $t = 500$ in Figure 2 and around $t = 550$ in Figure 3. In any case, the fit is much better than that obtained by either Falmagne (1968) or by Lupker and Theios (1975) in Experiment 2. The reader should also bear in mind that when approximating these functions by histograms, as we have done, the specific intervals chosen can have some influence on the shape of the curves. A close look at Figures 2 and 3 reveals that our second property of binary mixtures is not satisfied in either figure by the distribution of the stimulus having the largest presentation probability. The points to consider are $t = 475$ in Figure 2 and $t = 525$ in Figure 3, where this distribution dips below other distributions of less probable stimuli. It should also be noted that it is precisely this distribution in both cases which seems to be causing the problem with the fixed point property. The reader should also note that in Falmagne's (1968) data (see Figure 1) this distribution seems to be especially out of line. In addition, it is worth mentioning that this property is also violated in the data of Lupker and Theios (1975, see their Figure 1).

To check the Sternberg (Note 3) Long Reaction Time property, it is only necessary to observe whether the distribution

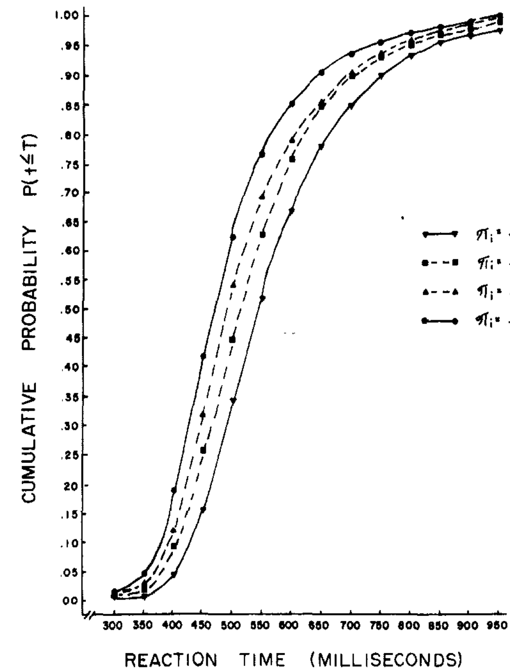

Figure 4. Obtained cumulative distribution functions for the four-choice reaction time task (since none of the four curves cross anywhere, they thus satisfy Sternberg's, Note 3, Long Reaction Time property).

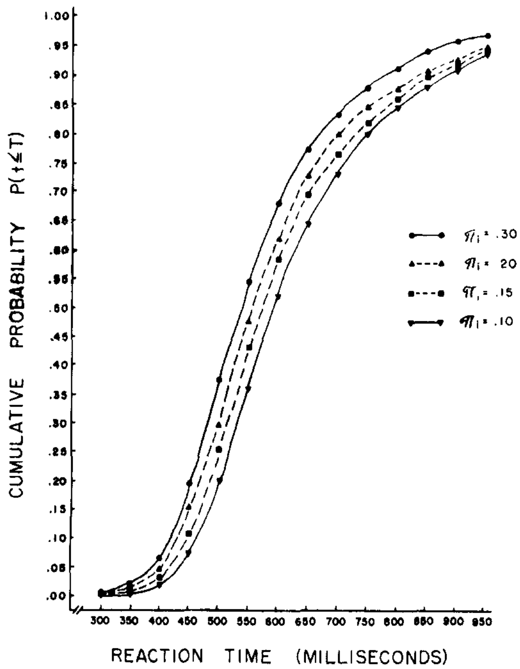

Figure 5. Obtained cumulative distribution functions for the six-choice reaction time task (since none of the four curves cross anywhere, they thus satisfy Sternberg's, Note 3, Long Reaction Time property).

functions cross at any point. The reader can see by looking at Figures 4 and 5 that none of the distribution functions cross in either the four- or six-choice tasks. Thus, Sternberg's Long Reaction Time property is not violated.

To evaluate the Link et al. (Note 4) distributional property, it was deemed wise to choose the three most reliable empirical distributions and to regard with caution those values of t quite distant from the middle of the distributions (500 msec for the four-choice task and 550 msec for the six-choice task). The reason for this is we are considering here a statistic which is a ratio. Therefore, when the denominator, $G_k(t) - G_j(t)$, becomes quite small (as happens at either large or small values of t), the effect of sampling variability becomes profound. For the four-choice task this meant letting $G_i(t)$ be generated by the stimulus with presentation probability .30, letting $G_j(t)$ be generated by the stimulus with presentation probability .20, and letting $G_k(t)$ be generated by the stimulus with presentation probability .40. The ratio should then be as follows:

$$\frac{G_i(t) - G_j(t)}{G_k(t) - G_j(t)} = \frac{\pi_i - \pi_j}{\pi_k - \pi_j} = \frac{.30 - .20}{.40 - .20} = \frac{1}{2}.$$

For the six-choice task, $G_i(t)$ was generated by the stimulus with presentation probability .20, $G_j(t)$ was generated by the stimulus with presentation probability .15, and $G_k(t)$ was generated by the stimulus with presentation probability .30. The ratio should then be as follows:

$$\frac{G_i(t) - G_j(t)}{G_k(t) - G_j(t)} = \frac{\pi_i - \pi_j}{\pi_k - \pi_j} = \frac{.20 - .15}{.30 - .15} = \frac{1}{3}.$$

The fit of the data to the ratio predictions is presented in Table 3 and seems reasonably good especially for the six-choice data.

Errors

Error reaction times were not included in the above analysis. As stated, if any session had more than 5% errors overall (i.e., 15 errors in 300 trials), it was immediately rerun. This restriction, along with our instructions to the subjects which emphasized accuracy, served to keep the error rate between 2% and 4% in over 75% of the sessions. It was hoped, of course, that error rates would be unrelated to presentation probability. However, this appears not to be the case. While the

Table 3
Observed Values of the Link, Ascher, and Heath Ratio for Both Four- and Six-Choice Tasks

t	Four-choice obtained ratios	Six-choice obtained ratios
375	.67	.47
425	.60	.49
475	.48	.34
525	.54	.40
575	.69	.35
625	.80	.44
675	.92	.41
725	.83	.41
775	.75	.34
825	.50	.26
875	.50	.25

Note. The predicted four-choice ratio was .50. The predicted six-choice ratio was .33.

trend is necessarily very slight because of the 5% limit, error rate did increase as presentation probability decreased in both tasks. In the four-choice task, the error rates were .020, .025, .032, and .049 for presentation probabilities .40, .30, .20, and .10, respectively. In the six-choice task, the error rates were .016, .029, .035, and .052 for presentation probabilities .30, .20, .15, and .10, respectively. However, because of the truly small differences in error rates, the effect this could have had on the data appears to be minimal.

Discussion

While the predictions of the model with respect to mean and sequential reaction times are not outstanding, they are suggestive. Specifically, the model constantly underpredicts the alternation (101) sequence, as the reader can see in Tables 1 and 2. Generally, there was no difference between the reaction time to that sequence and the reaction time to the double nonrepetition sequence (001). To our knowledge, this seems to be a very rare result in reaction time studies. In fact, Laming (1973) has found the reaction time to the alternation sequence is, at times, faster than the reaction time to the single repetition sequence (011) in a two-choice task. Other investigators (e.g., Lupker & Theios, 1975; Remington, 1969) have generally found the reaction time to the alternation sequence to be intermediate between the reaction times to the 011 and 001 sequences.

Falmagne et al. (1975), however, also obtained the same result we did with one of their three subjects in a two-choice task but only for the least probable stimulus. Why this result obtains in certain instances and not in others is unclear, though a general rule seems to be emerging. When considering second-order sequential reaction times, the difference between the two *nonrepetition* sequences [RT(001) − RT(101)] is smaller than the differences between the two *repetition* sequences [RT(011) − RT(111)] when a stimulus' presentation probability is small. However, when the presentation probability is large, the first difference becomes larger than the second. In our study with small presentation probabilities, RT(001) − RT(101) was essentially pushed to zero. Theoretically, if one stimulus was presented often enough it may be possible to drive the difference RT(011) − RT(111) to zero. There would, of course, be other variables of importance, for example, the length of the response–stimulus interval, so that in practice this may not be possible.

It should be noted, however, that even if this discrepancy between observed and predicted reaction time for the alternation sequence is a real one, this reflects only on the change of state assumption (3) and not on the idea of two states of preparation itself. A direct test of the two-state assumption can be obtained by looking at the distributional properties. The change of state assumption was necessary to derive the asymptotic probability of being prepared for any given stimulus, p_i. As shown, the fixed point property must hold regardless of the values of p_i used. The other distributional properties are more or less independent of the values of p_i. That is, as the reader can see by examining Equation 4, since p_i is a monotonic function of π_i, both the second property of distribution functions and Sternberg's (Note 3) Long Reaction Time property must still obtain. Finally, if p_i is a linear function of π_i (a not too unreasonable supposition), the Link et al. (Note 4) ratio $[G_i(t) - G_j(t)]/[G_k(t) - G_j(t)]$ is still equal to $(\pi_i - \pi_j)/(\pi_k - \pi_j)$. That is,

$$\frac{G_i(t) - G_j(t)}{G_k(t) - G_j(t)} = \frac{p_i - p_j}{p_k - p_j} = \frac{a\pi_i + b - (a\pi_j + b)}{a\pi_k + b - (a\pi_j + b)} = \frac{\pi_i - \pi_j}{\pi_k - \pi_j}.$$

Conclusions

While the two properties for cumulative distribution functions (Link et al., Note 4, and Sternberg's, Note 3, Long Reaction Time property) seem to be born out quite well in the data, there are two aspects of the data the model does not totally capture. First of all, we have begun to have doubts about the ability of the data to satisfy the two properties of density functions outlined earlier. In particular, the empirical reaction time distribution of the stimulus which is presented most often (whatever that presentation probability might be) seems to be transposed left from where it should be if the model were correct. Second, the model fails badly in predicting reaction time to the alternating stimulus sequence (101) which we found to be essentially no different from the reaction time to the double nonrepetition stimulus sequence (001). The model does, however, yield adequate predictions of the mean, first-order, and most second-order sequential reaction times.

Falmagne et al. (1975) have recently tested an extended version of the two-state model which attempts to account jointly for proportion of errors and error reaction times. Overall, their results were quite similar to ours. That is, while they found the general pattern of results to be consistent with the model, some specific deviations were observed. They concluded that some of the parameters they had assumed were invariant seemed to vary as a function of the stimulus presentation probability. Whether this will work in our situation is somewhat doubtful. The properties of the empirical density functions discussed above are independent of the parameter values chosen. In addition, finding equal reaction times for the alternation and double nonrepetition sequences while at the same time finding large reaction time differences between the double repetition (111) and single repetition (011) sequences cannot be explained by a judicious selection of parameter values. The obvious step of dropping the $a = a'$ assumption was unsuccessful, as the loss in degrees of freedom in no way made up for the slight improvement in the predictions.

What these two problems might indicate is that the underlying process is not a two-state but a three-state process in which the first state is a kind of superpreparation state. (A model of this sort is also discussed by Falmagne et al., 1975.) Briefly, since the probability of being superprepared for a particular stimulus would be a monotonic function of that stimulus' presentation probability, this would explain why the most probable stimulus yielded a distribution shifted a bit left. Or, perhaps a more general form of the three-state Falmagne and Theios (1969) model would adequately describe the data.

In any case, we feel that overall the distributional properties of the two-state model were not badly violated in the data; we see no reason as yet to reject the two-state assumption as a simple, heuristic model of the processes involved in these choice reaction time tasks. The two-state model should serve as a useful tool in answering some of the basic questions regarding the temporal properties of human choice behavior.

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