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Tests of Two Classes of Models for Choice Reaction Times

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Two experiments were designed to test a number of finite-state, self-terminating memory-scanning models for choice reaction times. The first class of models considered may be conceptualized as using probabilistic push-down stack memory mechanisms. Two-state and four-state models of this class were investigated. The other class of models tested was represented by a three-state model which assumed that the memorial stimulus–response associations could be found in one of three distinct states: high expectancy, short-term memory, or long-term memory. Four stimuli and responses were used in Experiment 1 and six were used in Experiment 2. In order to obtain tractable solutions to the predictions from the push-down stack models, each subject had one stimulus designated as the "key" stimulus, which was presented with probability π. The remaining stimuli were all presented with probability $(1-\pi)/3$ in Experiment 1 and probability $(1-\pi)/5$ in Experiment 2. In both experiments, the independent variable was π, which was varied as .10, .25, .40, .55, and .70. The data (mean reaction time, sequential reaction time, and distributional fixed-point property) uniformly supported the two-state model (which in fact lies in the intersection of the two classes of models investigated).

As early as 1885 Merkel reported the effect of the presentation probability of a stimulus on reaction time (RT): If stimulus A is presented more often than stimulus B, mean RT will be faster to stimulus A than to stimulus B. The explanation of this finding is a major focus of this research. Other effects in choice RT which must be accounted for are the sequential effects found by many investigators (e.g., Remington, 1969; Smith, Chase, & Smith, 1973). Falmagne (1965) proposed one of the first theoretical models of choice RT. He assumed two theoretical distributions underlying the empirical RT (one for each of two states of preparation). The RT was either a sample from the distribution with a smaller mean if the subject was "prepared" for the presented stimulus or a sample from the distribution with a larger mean if the subject was "unprepared" for the presented stimulus. The assumption was made that the subject could be prepared for more than one stimulus at a time. The difference between the means of the two distributions can be thought to occur because the subject first scans in parallel the memory representations of the stimuli for which he is prepared and then scans in parallel the other stimulus representations. The scanning process terminates after the first scan if the subject is prepared for the stimulus. Thus, the difference between the means of Falmagne's two distributions is the time necessary to complete the second parallel scan.

This two-state model was able to give good predictions of mean RTs, variances, and repetition effects, using a one-to-one stimulus–response mapping in a six-stimulus choice RT task with presentation probabilities of .56, .24, .10, .06, .03, and .01. Fal-

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magne (1965) did not investigate sequential effects in general, only the effects of the simplest sequentials, repetitions and nonrepetitions.

However, Falmagne (1968) has demonstrated a property of all two-state RT models that his own data from the six-choice experiment fail to satisfy. Assume two continuous overlapping distributions of RT. Let the prepared distribution be represented by $f(t)$ and the unprepared distribution by $g(t)$. Because of the overlap, there exists a point t_0 where the probability densities of the two distributions are equal, i.e., $f(t_0) = g(t_0)$. Let the common value be called x. For any given stimulus, on a proportion α of the trials RT will be a sample from $f(t)$, and on a proportion $1 - \alpha$ of the trials RT will be a sample from $g(t)$. Letting $h(t)$ equal the total reaction time distribution for any stimulus, we can write $h(t) = \alpha f(t) + (1 - \alpha)$ $g(t)$. Therefore, $h(t_0) = \alpha f(t_0) + (1 - \alpha)$ $g(t_0) = f(t_0) = g(t_0) = x$. This is true for all stimuli; at t_0 the density of the RT distribution for all stimuli has the same value, x. Intuitively, this means that if the two-state model is correct, there should exist a small interval of RT where all the empirical RT distributions, the $h(t)$s, have the same proportion of cases, independent of the stimulus or other variables such as presentation probability. For Falmagne's six-choice reaction time experiment, the six empirical RT distributions do not satisfy this fixed-point property.

This problem (which is inherent in any two-state model) led Falmagne and Theios (1969) to develop a three-state model to account for choice RT data. Each stimulus was hypothesized to have a representation that could reside in one of three memories, which corresponded to the three states. The three states were a *selective attention state,* which would hold only one stimulus representation, an *immediate memory state,* which could hold the representations of a number of stimuli (a possibly unlimited capacity state), and a *long-term memory state* (LTM), where all of the stimulus representations could be found if they were not found earlier in either of the other states. On any trial the selective attention state was searched first, then the immediate memory state, and finally LTM. Differences in RT occurred because the search terminated when the stimulus representation was found. Each state was hypothesized to have its own distribution (possibly normal) of total RT. This model is mathematically very tractable, and Falmagne and Theios were able to derive asymptotic probabilities for the representation of any given stimulus being in each of the three states.

This model was fitted to data from Falmagne's (1965) six-choice experiment, using Chandler's (1969) subroutine STEPIT to find the best estimates of the parameters. The authors judged that the fit of the predicted reaction time distributions to the observed distributions for all six of the stimuli was close enough to warrant further investigation of this type of model.

The three-state model led Theios (1973) to the development of a push-down stack model, which postulates a short-term memory buffer that is searched position by position in a serial, self-terminating manner. The expected comparison time for an S–R association in the nth position is n times the mean of the hypothesized scanning time distribution (which is called the mean comparison time for one memory position). The actual comparison time for each position is assumed to be a random sample from the scanning time distribution.

The model fails immediately if the memory buffer is postulated to have an unlimited capacity. Evidence for this is provided by Theios (1973). According to the model, mean choice RT should be linear with the number of stimuli if all of the stimuli have the same presentation probability. Theios found that linearity held only to about four to six stimuli. After that, RT no longer increased linearly as the number of stimuli increased. To account for this fact Theios hypothesized that all the S–R associations are stored in LTM and that a search of LTM commences as soon as the stimulus has been encoded. The LTM search is conducted at the same time as the buffer scan; if the buffer search has not produced the S–R association by the time the LTM search is completed, finding the association in LTM terminates the buffer search, and the system proceeds to a response stage. An analysis was undertaken to find the average position of the buffer search at the time of interruption. This was done by taking data from two-, four-, six-, and eight-stimuli choice RT tasks and plotting reaction time as a function of expected buffer position, conditional on a termination after two, three, four, five, or six stimuli have been scanned. Since RT was linear with expected buffer position only for a model with four memory positions, it was decided to further test the push-down stack model in which only the first four positions in the buffer were scanned before LTM found the S–R association. Mathematically, the buffer can be thought of as consisting of four positions; the first three contain only one S-R association, while the remaining S–R associations are "packed" into the fourth position (LTM), which is searched in parallel.

Theios' (1973) estimate of the buffer capacity as four S–R associations led Lupker (1974) to derive a mathematically tractable version of the four-state push-down stack model. Lupker found that for the special case where one stimulus is presented with an arbitrary probability π and the remaining n stimuli are presented with equal probabilities of $(1-\pi)/n$, analytic solutions could be obtained for the asymptotic probability of an S–R association being in each of the four memory positions. The purpose of the experiments reported here was to test Lupker's special case of the four-state model, and to compare it to Falmagne and Theios' (1969) three-state model and Falmagne's (1965) two-state model. In Experiment 1 four stimuli were used in order to provide a test where all S–R associations fit into the serial scanning buffer. In Experiment 2 six stimuli were used to provide a test where the buffer capacity is exceeded.

Method

Subjects. In Experiment 1 the subjects were 20 right-handed student volunteers from the University of Wisconsin—Madison. The subjects by chance consisted of 10 males and 10 females. In Experiment 2 there were 30 right-handed subjects, 16 females and 14 males.

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). An Industrial Electronics Engineers Inc. (Series 10) rear-projection visual readout unit was mounted in a console at eye level approximately .6 m in front of the subject. The chair and visual read-out unit were enclosed in an Industrial Acoustic Co. (Model 410A) sound-attenuating room. To further mask outside noise the subject wore earphones (Elga Model DR-66C) that delivered wide-band white noise at 70 mV generated by a Grayson-Stadler (Model 901B) noise generator. The stimuli were the white digits 3, 4, 5, 6, 7, and 8 (approximately 2.56 cm tall) presented on a 3.2×3.2 cm green background. A Digital Equipment Corporation PDP-8 computer was programmed to present the stimuli and to record on magnetic tape the stimulus, response, and reaction time for each trial.

Procedure. There were five conditions in each experiment. In each condition, one of the stimuli (the key stimulus) was presented on any trial with a fixed probability π, while the remaining n stimuli were each presented with probability $(1-\pi)/n$. In Experiment 1, $n=3$ stimuli and in Experiment 2, $n=5$ stimuli. The five key stimulus probabilities used were .10, .25, .40, .55, and .70. Within-subjects designs were used, as each received all five conditions in a single experimental session.

In Experiment 1 the stimuli were the digits 4–7, and four 5×5 Latin squares were used to determine the order of the conditions for each of the 20 subjects. The key stimulus was held constant for any particular subject, with each digit being the key stimulus for 25% of the subjects. In this way every stimulus occurred equally often over the course of the experiment.

In Experiment 2 the stimuli were the digits 3–8, and six 5×5 Latin squares were used to vary the order of presentation of the conditions for each of the 30 subjects. Each subject had one key stimulus throughout the experiment, and each stimulus was the key stimulus for one sixth of the subjects.

A trial consisted of one of the stimuli being randomly selected according to the assigned probabilities and then being presented to the subject. The stimulus would remain on until a response was made. The response–stimulus interval was 500 msec, and there was a sequence of 304 stimuli in each condition for each subject, giving 1,520 responses from each subject. Any condition with more than 5% errors was run again before the subject proceeded to the next condition, and there was a 3- to 5-min rest between conditions. 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, 8–right ring finger.

Experiment 1

Results

Mean RT. The two-state and four-state models predict that mean RT to a particular

TABLE 1

OBSERVED AND PREDICTED MEAN REACTION TIMES (IN MSEC) FOR ALL CONDITIONS IN EXPERIMENT 1

π	No. observations[a]	*SE*	Observed	Predicted by 2-state	Predicted by 3-state	Predicted by 4-state
			Key stimuli			
.10	608	75	548	568	574	585
.25	1620	63	530	534	537	531
.40	2632	65	504	500	501	496
.55	3644	50	462	467	465	470
.70	4856	50	427	434	429	451
			Other stimuli			
.30	6372	61	538	523	525	513
.25	5360	48	542	534	537	531
.20	4348	52	553	545	549	543
.15	3336	51	557	557	562	552
.10	2324	54	561	568	574	558
RMSE				10	11	17
r				.97	.97	.91
X^2				4	5	15
df				8	6	8
p				$.95 > p > .9$	$.9 > p > .8$	$.2 > p > .1$

[a] This column represents the expected number of observations contributing to each mean.

stimulus will be linearly related to the theoretically expected position of that stimulus's S–R association in memory. Under the assumption that upon the presentation of a stimulus whose S–R association is not in the first ("prepared for") position in memory, the probability of that stimulus's representation moving into the "prepared for" position is a constant a for all stimuli, the expected position of each stimulus representation with respect to the two-state model can be determined by $\pi 1 + (1 - \pi)2$. The asymptotic probabilities of being in each state for the four-state push-down stack model were calculated by raising the transition matrix to an asymptotic power. Letting P_j equal the asymptotic probability of an S–R association being in position j of the stack, the expected position was then defined as:

$$\sum_{j=1}^{4} j \cdot P_j.$$

To get predictions of mean RT for these two models, obtained mean RT was plotted against expected position for the 10 points representing the observed mean RTs of the five key stimuli and the pooled mean RTs of the other stimuli in each of the five conditions; the best-fitting straight line was then drawn through these 10 points. The best-fitting line was the one that produced the smallest root mean squared error (RMSE) between the observed points and the line. The predicted and observed mean RTs are given in Table 1. As is clearly visible from looking at the RMSEs and the correlation coefficients (r) between observed and predicted mean RT, the two-state model accounts for the trend of mean RT much better than the four-state model ($r = .97$ and $.91$; RMSE $= 9.5$ and 17.2, respectively). In solving for the parameters of the two-state model, the mean of the "prepared for" distribution was empirically determined to be 368 msec and the mean of the other distribution, 588 msec. In solving for the parameters of the four-state model it was determined that the intercept of the line relating mean RT to expected memory position was 356 msec and the slope (scanning rate) was 70 msec.

An interesting thing happened with Falmagne and Theios' (1969) three-state model.

TABLE 2

Observed and Predicted Sequential Mean Reaction Times (in msec) Pooled over All Conditions in Experiment 1

Sequence	No. observations	*SE*	Observed	Predicted by 2-state	Predicted by 3-state	Predicted by 4-state
01	5578	67	522	519	527	489
11	5904	54	426	426	424	443
001	3210	71	543	546	558	566
011	2604	56	457	457	460	454
101	2368	69	493	487	489	456
111	3300	60	402	403	397	434
RMSE				3	8	27
X^2				26	25	134
df				27	25	27
p				$.7 > p > .5$	$.8 > p > .7$	$p < .001$

It was fit to the data using STEPIT to estimate means for the three RT distributions and the parameter d.[1] The RMSE was lowest when the means of the second and third distributions were equal. What this means is that only two distributions are needed to give the best description of the data. In other words, the three-state model collapsed into a two-state model when fit to the data. The predictions from this model can also be found in Table 1. The difference in quality of fit between this and the two-state model is negligible and is due only to the fact that STEPIT yields nondeterministic parameter estimates.

Though the computation of RMSE is a generally used method for evaluating the fit of these models to data, it is also necessary to show by means of a goodness-of-fit test that the fit is acceptable with respect to statistical standards. Therefore a test which is currently being used by Falmagne, Cohen, and Dwivedi (1975) for evaluating this type of model was employed. In the last three rows under each model in Table 1 are the X^2 values for that model, the degrees of freedom, and the probability of obtaining that value from a χ^2 distribution (p values). The test casts some suspicion on the four-state model.

Sequential effects. At this point it appears that the data are pointing very strongly towards the two-state model. However, it is necessary to look at how well the different models predict sequential RTs. Mean RTs conditional on the preceding sequence of stimuli are presented in Table 2. A seqeunce is represented by a series of zeros and ones; 0 indicates that the stimulus under consideration was not presented on that trial and 1 indicates that the stimulus was presented on that trial. The order of presentation is left to right, and the RT under consideration is from the trial identified by the 1 that is always in the farthest right position in the sequence. For the two-state model and the three-state model (reduced to two states), STEPIT was used to estimate the value of the parameter a (a is the probability of a stimulus's S–R association moving into the first state after a presentation of that stimulus when it was not originally in the first state). Averaged over all conditions, the predictions of these two models for the conditional mean RTs are also given in Table 2. In addition STEPIT was also allowed to derive predictions for the four-state model by estimating the optimal set of the three parameters: a, scanning rate, and the intercept of the straight line relating RT to expected position. The predictions of the four-state model (averaged over all conditions) are also given in Table 2.

The χ^2 tests described earlier were also performed on the sequential data. For each model, an analysis was performed on the 30 predictions, one prediction for each of the six sequences at each of the five conditions.

[1] The parameter d represents the probability of a stimulus-response association in immediate memory dropping into long-term memory on a trial when the corresponding stimulus is not presented.

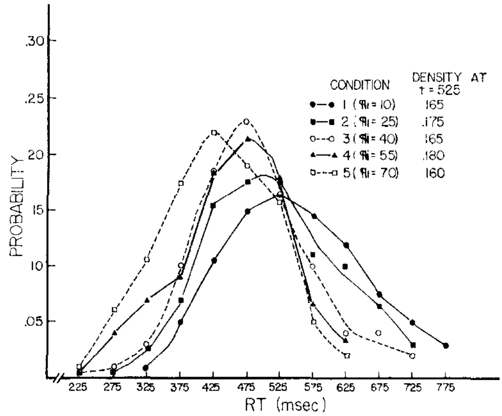

FIGURE 1. Empirical reaction time distributions for the five key stimuli in Experiment 1: probability (relative response frequency) as a function of reaction time (RT).

The χ^2 values and their associated probabilities can be found in Table 2 under the predictions for each model for the averaged sequentials. The analyses permit rejection of the four-state model.

Fixed-point property. The RT distributions for the five key stimuli are shown in Figure 1. As can be seen clearly, the five distributions all cross in a small interval in the neighborhood of $t = 525$ msec. The probability density estimates (relative freqencies) for the RT interval from 500 to 550 msec for each of the five distributions are also shown on the figure. Therefore, one must conclude that the examination of the data with respect to the fixed-point property provides no evidence for rejection of the two-state model.

Discussion

Two-state model. The fit of the two-state model to the data is indeed impressive. However, it was not entirely unexpected, as the two-state model has been shown to fit data from other choice RT experiments (Theios & Smith, 1972). A further piece of evidence that the two-state model is the most appropriate model for this task is the fact that the three-state model yielded its best predictions when the means of States 2 and 3 were equal, meaning that two states account for the data better than three.

Four-state model. The version of the four-state model that was rejected had its assumptions chosen in such a way that it became mathematically tractable. In the general model of Theios (1973) the assumptions are much less rigid. As a function of the assumptions made in the present paper, the predictions for the stimulus sequences 101 and 011 are nearly the same, whereas the observed means for these points are generally quite disparate. These two points account for much of the total disparity among the observed and predicted RTs in each condition. The closeness of the two predictions is probably necessitated by the assumption that the probability of an S–R association moving up to a given state upon stimulus presentation (given that it did not move into a higher state) is the same for all states. The consequences of relaxing this restriction by introducing two new parameters (one for the probability of moving up to State 2 given that the S–R association did not move into the first state and one for the probability of moving up to State 3 given that the S–R association did not move into States 1 or 2) cannot presently be determined. However, this consideration probably reaches the heart of the problem with the specific version of the four-state model tested here. In any event, the rejection of this specific version of the four-state model does not imply the rejection of the general form of the push-down stack theory, since the two-state model is a special case of the push-down stack theory.

EXPERIMENT 2

Falmagne (1968) has shown that the data from his six-choice reaction time task (1965) are very much at odds with the two-state interpretation presented in the first part of this article. His six reaction time distributions fail to demonstrate the fixed-point property of binary mixtures, as discussed earlier. Although Falmagne did not report a statistical test, graphs of the six distributions, one below another, very clearly show that the fixed-point property fails badly. There are several possible explanations for the differences between the findings of Falmagne (1968) and those of the present experiment. One is that the stimuli with the three smallest presentation probabilities in Falmagne's experiment did not occur often enough to yield a good description of the actual reaction time distributions of those three stimuli. These three stimuli were presented with small probabilities of .06, .03, and .01, yielding only 720, 360, and 120 stimulus–response occurrences, respectively, to determine the empirical RT distributions. It is precisely these three distributions which caused Falmagne to reject the two-state model. Plainly, more observations are needed as well as a statistical test of the fixed-point property in order to clearly reject the two-state model.

Second, it could very well be that Falmagne is on firm ground in rejecting the two-state model for his task but that his experiment and Experiment 1 reported here tap two different processes. The three-state model of Falmagne and Theios (1969) best illustrates this idea. Suppose the three-state model is correct. In Falmagne's six-choice experiment the subject holds one S–R association in the selective attention state and then loads immediate memory with as many other S–R associations as it will hold. If the capacity of immediate memory is less than five, there is at least one association (S*–R) which must be retrieved from LTM. When S* occurs, RT would come from a third, LTM distribution. However, suppose also that the capacity of immediate memory is greater than two. In Experiment 1, which used four stimuli, one S–R association would be held in selective attention and three in immediate memory. Therefore, all RTs would be drawn from one of only two distributions. Experiment 2 was designed to test this hypothesis. Following the same format as in Experiment 1, with one key stimulus with a given presentation probability π and the other n stimuli each presented with probability $(1-\pi)/n$, n was raised from three to five. If the suppositions are indeed correct, immediate memory should then be overloaded and the three-state model should give a better account of the data than the two-state model.

As an alternative hypothesis, it could be the case that with six stimuli subjects' method of organizing memory breaks down altogether, so that they adopt instead the search strategy as outlined in Theios (1973), arranging the stimuli in a stack and on each trial scanning the stack in a serial, self-terminating fashion. Therefore, the data from Experiment 2 will also be analyzed in the framework of a four-state version of the stack model, as was not done with Falmagne's (1965) six-choice RT data.

Results

Mean RT. The predicted and observed mean RTs for Experiment 2 are given in Table 3 along with the RMSEs and the correlation coefficient between obtatined and predicted means for each model. The means of the two theoretical distributions for the two-state model were determined to be 353 msec and 685 msec. The two parameters of the four-state model, scanning rate and intercept, were found to be 100 msec and 333 msec, respectively.

Predictions for mean RT for the three-state model were again obtained by using STEPIT to estimate the four parameters (i.e., the three means and d), and the predictions can also be found in Table 3. Unlike Experiment 1, the three-state model did not reduce to two states, and the values of its four parameters were $\mu_A = 403$ msec, $\mu_I = 540$ msec, $\mu_L = 702$ msec, and $d = 1.0$.

It is immediately obvious from looking at the RMSEs and the correlation coefficients that the three models provide equally good fits to mean RT. Falmagne's χ^2 test (which was described earlier) was performed on the three sets of predictions. The X^2 values as well as the probability of obtaining that value from a χ^2 distribution with the appropriate number of degrees of freedom (p values) can also be found in Table 3 under the appropriate model. As is quite obvious, there is little information in mean RT to enable one to choose among the three models.

Sequential effects. Sequential mean RTs were also analyzed in the same way as in Experiment 1. STEPIT twice estimated values of the transition parameters of each model. The first time was done under the assumption that the transition parameters varied across conditions and the second time under the assumption that they did not. The observations and predictions (averaged over

TABLE 3

OBSERVED AND PREDICTED MEAN REACTION TIMES (IN MSEC) FOR ALL CONDITIONS IN EXPERIMENT 2

π	No. observations[a]	*SE*	Observed	Predicted by 2-state	Predicted by 3-state	Predicted by 4-state
			Key stimuli			
.10	912	119	653	652	652	657
.25	2280	102	589	602	601	583
.40	3648	74	543	552	551	533
.55	5016	70	494	502	502	498
.70	6484	72	461	453	454	471
			Other stimuli			
.18	8108	112	654	625	625	627
.15	6746	89	647	635	635	642
.12	5372	102	647	645	645	652
.09	4004	98	651	655	655	659
.06	2636	99	647	665	666	663
RMSE				13	13	12
r				.98	.98	.99
X^2				5	5	4
df				8	6	8
p				$.8 > p > .7$	$.7 > p > .5$	$.9 > p > .8$

[a] This column represents the expected number of observations contributing to each mean.

all conditions) for the second- and third-order sequential mean RTs can be found in Table 4 along with the RMSE for each set of predictions.

As in Experiment 1, χ^2 analyses were done for each model on the 30 predictions (six sequential mean RTs for each of the five conditions). The X^2 values were significant for every model except the two-state model, with separate values of the parameter a estimated for each condition. The X^2 and corresponding p values can be found under the appropriate model in Table 4.

Fixed-point property. Once again the predictive power of the two-state model surpasses that of the other two models. This fact again raises the question of whether the RT distributions satisfy the fixed-point property of Falmagne (1968). Figure 2 contains the RT distributions of the five key stimuli.

TABLE 4

OBSERVED AND PREDICTED SEQUENTIAL MEAN REACTION TIMES (IN MSEC) POOLED OVER ALL CONDITIONS IN EXPERIMENT 2

Sequence	No. observations	*SE*	Observed	Predicted by 2-state	Predicted by 2-state[a]	Predicted by 3-state	Predicted by 4-state
01	8551	95	577	584	579	570	554
11	8870	74	450	448	453	448	475
001	4936	105	604	625	621	612	633
011	3941	66	482	497	497	511	485
101	3615	91	540	532	526	518	490
111	4929	82	426	412	419	413	453
RMSE				13	11	16	30
X^2				51	33.2	68	114
df				27	23	25	27
p				$p < .01$	$.2 > p > .1$	$p > .001$	$p < .001$

[a] Separate a parameter estimated for each condition.

If Falmagne's fixed-point property obtains there should be a small interval where all of these distributions cross. There does seem to be an interval between 475 msec and 525 msec where all the distributions do appear to take on probability density (relative frequency) values near .17. However, the results are not as unequivocal as in Experiment 1. In any case, the data do show a much better fit to the fixed-point property than Falmagne's (1968) original data and do not cause one to seriously question the two-state interpretation based on this analysis.

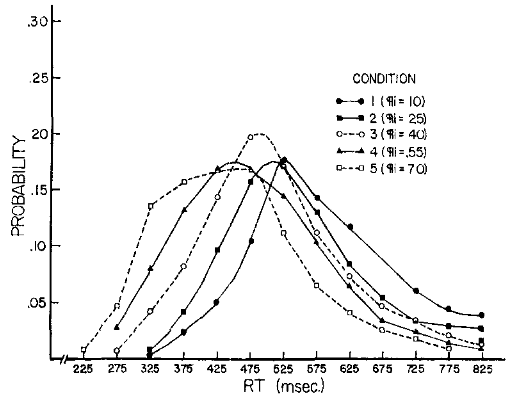

FIGURE 2. Empirical reaction time distributions for the five key stimuli in Experiment 2: probability (relative response frequency) as a function of reaction time (RT).

Discussion

As in Experiment 1, the fit of the four-state model to the sequential mean RTs was sufficiently poor to permit unequivocal rejection of this model. The fit of the three-state model to the sequential mean RTs was only slightly better, and the χ^2 analyses also permitted the rejection of this model. These results refute the explanation offered earlier to account for the discrepancies between the findings of Experiment 1 and Falmagne (1968). This explanation suggested that in Falmagne's task the subjects were not able to store all six S–R associations in the selective attention and immediate memory areas and were then forced to search LTM for the S–R association on some of the trials. In Experiment 1 only four stimuli were used, and it was hypothesized that the three S–R associations not in the selective attention state did not overload immediate memory and, therefore, that immediate memory could hold the representations of the remaining stimuli. Thus, LTM was not used and the RTs were always samples from one of two distributions. Because of this, the fixed-point property obtained in the data from Experiment 1 but did not obtain in Falmagne's data. However, it is obvious from the poor fit of the three-state model to the data of Experiment 2 that another explanation of the discrepancy is needed.

We would like to suggest that in Falmagne's experiment the RT distributions of the three stimuli with the largest presentation probabilities do show a reasonable approximation to the fixed-point property. However, the other three stimuli had presentation probabilities so small (i.e., .06, .03, and .01) and occurred so infrequently that the subject effectively "forgot" about them. On the trials when they did occur, the search then carried into long-term memory and a third distribution came into play. In Experiments 1 and 2 the smallest presentation probability of a key stimulus was .10 (the third largest probability in Falmagne's experiment), so that the forgetting problem did not arise in our experiments to any great extent. Therefore, the key stimulus distributions reasonably approximated the fixed-point property. In the case of the other stimuli in Experiments 1 and 2, the presentation probabilities did get as low as .06 in one condition. However, there were also four other stimuli with the same presentation probability, and there would be no reason to believe that subject would selectively "forget" any one particular stimulus while remembering the other four.

Michael Posner has suggested that the design of the present experiments may have contributed to the fact that the subjects organized memory into two states. Since there usually was a bimodal distribution of stimulus presentation probabilities with one relatively frequent stimulus and n relatively infrequent stimuli, the subjects may have categorized the set of stimuli into two subsets, one unique stimulus which typically had a high presentation probability and "all the others" which typically had lower presentation probabilities. The fact that the two-state model and the fixed-point property held could have been due to this type of dichotomization. If dichotomization of the stimuli in this specific design is responsible for the data supporting two states of responsiveness, then one might expect that key stimuli and other stimuli would differ in mean RT. A test of this hypothesis is provided by a 2 × 2 analysis of variance of a subset of the data from Experiment 1. Stimulus presentation probability (.25 and .10) is one factor, and type of stimulus (key and other) is the other. The main effect of stimulus probability was significant as expected, $F(1, 19) = 17.6$, $p < .001$. However, there was no significant difference in mean RT between key and other stimuli, $F(1, 19) = .025$. While the outcome of this test does not disprove Posner's suggestion, it is consistent with the predictions of the two-state model. On the other hand, if stimulus dichotomization caused the data to support the two-state model, the generality of the model for choice RT may be limited in scope. A direct test between this interpretation and the one we presented for the differences between our results and those of Falmagne (1968) could be made by conducting a six-stimulus choice RT experiment in which the presentation probabilities for the six stimuli varied, but never fell below .10.

In summary, the two-state model has been tentatively accepted as a heuristic model of the RT processes involved in Experiments 1 and 2. The data give strong support to this model and only provide a few pieces of evidence against it. The only obviously necessary modification is that the axioms for position change of S–R associations must be altered to explain how and why the transition probability a might vary with the presentation probability of a stimulus.

REFERENCES

Chandler, J. P. STEPIT: Finds local minima of a smooth function of several parameters. *Behavioral Science*, 1969, *14*, 81–82. (CPA 312)

Falmagne, J. C. Stochastic models for choice reaction time with application to experimental results. *Journal of Mathematical Psychology*, 1965, *12*, 77–124.

Falmagne. J. C. Note on a simple property of binary mixtures. *British Journal of Statistical and Mathematical Psychology*, 1968, *21*, 131–132.

Falmagne, J. C., Cohen, S., & Dwivedi, A. Two-choice reactions as an ordered memory scanning process. In P. M. A. Rabbitt & S. Dornic (Eds.), *Attention and performance V*. London: Academic Press, 1975.

Falmagne, J. C., & Theios, J. On attention and memory in reaction time experiments. In W. G. Koster (Ed.) *Attention and Performance II*. Amsterdam: North-Holland, 1969. (Reprinted from *Acta Psychologica*, 1969, *30*.)

Lupker, S. J. *Tests of three models of choice reaction times* (Report 74-2, Wisconsin Mathematical Psychology Program). Madison: University of Wisconsin, Department of Psychology, 1974.

Merkel, J. Die zeitlichen Verhältnisse der Willensthätigkeit. *Philosophische Studien*, 1885, *2*, 73–127.

Remington, R. J. Analysis of sequential effects in choice reaction times. *Journal of Experimental Psychology*, 1969, *82*, 250–257.

Smith, E. E., Chase, W. G., & Smith, P. G. Stimulus and response repetition effects in choice reaction time: Trace decay or memory search. *Journal of Experimental Psychology*, 1973, *98*, 413–422.

Theios, J. Reaction time measurements in the study of memory processes: Theory and data. In G. H. Bower (Ed.), *The psychology of learning and motivation* (Vol. 7). New York: Academic Press, 1973.

Theios, J., & Smith, P. G. Can a two-state model account for two-choice reaction time data? *Psychological Review*, 1972, *79*, 172–177.

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