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TECHNICAL REPORT NO. 52

January 29, 1963

PSYCHOLOGY SERIES

APPLIED MATHEMATICS AND STATISTICS LABORATORIES

STANFORD UNIVERSITY

STANFORD, CALIFORNIA

A TEST OF THREE MODELS FOR STIMULUS COMPOUNDING WITH CHILDREN*/

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A central issue in many current theories of learning deals with the problem of predicting behavior in the presence of a new stimulus compound that is constructed by combining component stimuli on which the subject has had previous discrimination training. As an example of the type of problem we have in mind, consider a situation where on each trial a subject is required to make either an A_1 or an A_2 response. If, after training, he tends to make A_1 with probability p_t on trials when a tone is presented, and with probability p_ℓ when a light is presented, then what will be the probability of an A_1 response when light and tone are presented simultaneously. Obviously the probability $p_{t\ell}$ of making A_1 to the compound stimulus (tone + light) will be at least partially dependent on the values of p_t and p_ℓ. In terms of general psychological considerations there are several plausible functions relating $p_{\ell t}$ to p_ℓ and p_t; the purpose of this paper is to determine which of these functions provides the best account of data collected in a prediction experiment using young children.

The experimental situation involves a series of 960 discrete trials for each subject. The trials are of two types: learning trials and test trials. Learning trials are initiated with the presentation of one

*/ This research was supported by the National Science Foundation (Grants 10041 and 24264) and by the National Institute of Mental Health (Grant MH-05184).

of three distinct stimuli; these stimuli are denoted s_1, s_2 and s_3. The subject is required to make one of two responses (A_1 or A_2) and the trial is then terminated with either an E_1 or E_2 reinforcing event. The occurrence of E_i means that A_i was the correct response for that trial. The schedule for presenting reinforcing events on learning trials is specified by the parameter π_i; when s_i is presented an E_1 occurs with probability π_i and an E_2 with probability $1-\pi_i$. Interspersed among the learning trials are test trials. On test trials one of the following four stimulus compounds is presented: (s_1+s_2), (s_1+s_3), (s_2+s_3) or $(s_1+s_2+s_3)$. The subject is required to make an A_1 or A_2 response to the presentation of the compound, but no reinforcing event is given.

We shall consider three models that yield predictions for responses in the presence of a stimulus compound. Let p_i denote the probability of an A_1 response to the presentation of s_i; p_{ij} the probability of A_1 to the presentation of the compound (s_i+s_j); and p_{123} the probability of A_1 to the compound $(s_1+s_2+s_3)$. The three models to be considered are as follows:

Model I

$$\begin{aligned} p_{ij} &= \omega\left[\tfrac{1}{2}(p_i+p_j)\right] + (1-\omega)\tfrac{1}{2} \\ p_{123} &= \omega\left[\tfrac{1}{3}(p_1+p_2+p_3)\right] + (1-\omega)\tfrac{1}{2} \end{aligned} \tag{1}$$

This hypothesis is derived from models of discrimination learning proposed by Burke and Estes (1957), Schoeffler (1954) and others. The first part of the right hand side of the equation states that each component stimulus contributes equally in determining the response to the compound; i.e., the probability of an A_1 response to the compound (s_1+s_2) is simply the average of p_1 and p_2. The second part of the equation allows for the possibility that there may be some regression toward random responding in the presence of a new stimulus compound. The parameter ω weights these two effects and we assume that the value of ω is the same for all stimulus compounds.

Model II

$$p_{ij} = \omega\left[\frac{c_i}{c_i+c_j}\, p_i + \frac{c_j}{c_i+c_j}\, p_j\right] + (1-\omega)\frac{1}{2} \;,$$

$$p_{123} = \omega\left[\frac{c_1p_1+c_2p_2+c_3p_3}{c_1+c_2+c_3}\right] + (1-\omega)\frac{1}{2} \;, \tag{2}$$

where $c_i = p_i\pi_i + (1-p_i)(1-\pi_i)$ and is the probability of a correct response (A_1E_1 or A_2E_2) on a trial on which s_i is presented. Here we assume that the influence of each component of a new compound is proportional to that component's relative likelihood of eliciting a correct response on previous trials. For example, if s_1 has elicited more correct responses than s_2 on previous learning trials, then the response to the compound (s_1+s_2) will be more influenced by the s_1 cue than by s_2. The present hypothesis can be derived from an observing response model (Atkinson, 1961) or from a perceptual process model for discrimination learning (Atkinson, 1960). Again, as for Model I, we assume that with weight $1-\omega$ there is a tendency to regress toward random responding in the presence of a new stimulus compound.

Model III

$$p_{ij} = \begin{cases} \omega p_i + (1-\omega)\frac{1}{2} & , \text{ if } c_i > c_j \\ \omega p_j + (1-\omega)\frac{1}{2} & , \text{ if } c_j > c_i \end{cases}$$

$$p_{123} = \begin{cases} \omega p_1 + (1-\omega)\frac{1}{2} & , \text{ if } c_1 > c_2 \text{ and } c_3 \\ \omega p_2 + (1-\omega)\frac{1}{2} & , \text{ if } c_2 > c_1 \text{ and } c_3 \\ \omega p_3 + (1-\omega)\frac{1}{2} & , \text{ if } c_3 > c_1 \text{ and } c_2 \end{cases} \tag{3}$$

(When equality holds in the relations among the c_i's, then apply Model I.) Here we assume that the response to a stimulus compound is determinded solely by the single component cue that has been most frequently associated with a correct response on previous trials. For example, if s_1 has elicited more correct responses than s_2, then $p_{12} = p_1$. Again, as for both of the previous models, we assume that with weight $1-\omega$ there is some regression toward a chance response level.

To illustrate predictions for each of these hypotheses consider a case in which $\pi_1 = 1$ and $\pi_2 = \frac{1}{2}$. Further, assume that $\omega = 1$ and that after a large number of trials p_1 approaches a fixed value of 1, and p_2 a value of $\frac{1}{2}$. Then $c_1 = 1$, $c_2 = \frac{1}{2}$ and the predicted value for p_{12} will be $\frac{1}{2}(1+\frac{1}{2}) = \frac{3}{4}$ by Model I, $\frac{2}{3}(1) + \frac{1}{3}(\frac{1}{2}) = \frac{5}{6}$ by Model II, and 1 by Model III.

METHOD

Subjects and apparatus. -- The subjects were 48 children (26 girls and 22 boys) from the University Elementary School; all subjects were in the fifth and sixth grade. They were randomly assigned to three groups with 16 per group.

The subjects were run in subgroups of two or three with each subject seated in a private booth. The apparatus, viewed from within the subject's booth, consisted of a shelf at table level that was 30 in. wide and 10 in. deep. A panel 30 in. wide and 28 in. high was mounted vertically on the back edge of the shelf. Three signal lights (the s_i stimuli) were in a horizontal row, centered on the vertical panel; the lights were 15 in. from the base of the panel and were spaced at 2 in. intervals. Two silent operating keys (the A_1 and A_2 responses) were each mounted 2 in. in from the front edge of the shelf; these keys were 14 in. apart. One inch behind each of the keys was mounted a white frosted panel light (the E_1 and E_2 events).

Experimental design. -- Each subject was run for 960 trials. In consecutive blocks of 96 trials, there were 72 trials where s_1, s_2, and s_3 occurred equally often; on the remaining 24 trials the compounds (s_1+s_2), (s_1+s_3), (s_2+s_3), and $(s_1+s_2+s_3)$ occurred equally often. Thus, for example, in every 96-trial block s_1 was presented 24 times and (s_1+s_2) was presented 6 times. Otherwise, the presentation order of stimulus events was randomly determined for each subject.

Three main groups were run. For all groups $\pi_1 = 1$ and $\pi_2 = \frac{1}{3}$. The groups differed with respect to the value of π_3. For Group 1 $\pi_3 = \frac{1}{4}$; for Group 2, $\pi_3 = \frac{1}{2}$; and for Group 3, $\pi_3 = \frac{3}{4}$. Within each of the main groups, two subgroups of eight subjects were formed by counterbalancing the right and left positions of the response keys.

Procedure. -- For each subject one of the three signal lights was randomly designated s_1, another s_2, and the remaining one s_3. The subjects were read the following instructions:

"This is an experiment to find out how good you are at guessing. It may be very much like other guessing games you've played before. Take a look at the board in front of you. One or more of the top lights goes on every few seconds. Also note the two buttons with a light over each. When the experiment starts, and one or more of the top lights goes on, you are to guess which of the bottom two lights will follow. You do this by pressing the button under the light you think will follow. If you think the left light will go on, press the left button; if you think the right light will go on, press the right button. Remember, as soon as one or more of the top lights goes on, press the button on the side on which you think a light will go on, and see how many times you can guess correctly. Be sure to make your guess as soon as the top light or lights goes on. If you are right a light will go on over the button you have pressed. If you were wrong, a light will go on over the other button. Try to make as many correct guesses as possible. Sometimes no light will appear over either button, but still you should have made a guess because you may have been correct. You will not know which one was correct but we are still keeping score. Now be sure to press the button as soon as the top light or lights goes on and try to get as many correct as possible, but be sure to press one button every time. Are there any questions?"

Questions were answered by paraphrasing the appropriate parts of the instructions. Following the instructions, 240 trials were run in continuous sequence. This was followed by a 5 minute rest period. After the rest, an additional 240 trials were run. All subjects were required to return the next day and another 480 trials were run with a 5 minute break between the first and last 240 trials. Thus each subject was run a total of 960 trials.

On all trials the signal light(s) was lighted for 3 sec.; the time between successive signal onsets was 6 sec. The E_1 or E_2 light (if lighted) went on immediately following the offset of the signal light and remained on for 2 sec. The presentation of stimulus and reinforcing events and the recording of responses were automatically controlled.

RESULTS AND DISCUSSION

Mean learning curves and asymptotic results. -- The top panel of Figure 1 presents the proportion of A_1 responses on s_1 trials in successive 96-trial blocks. For each subject the proportion of A_1 responses on s_1 trials was tabulated for a 96-trial block, and these quantities were averaged over subjects. Similarly, the middle and bottom panels of Figure 1 present the proportion of A_1 responses on s_2 and s_3 trials, respectively. In all three panels the curves appear to be reasonably stable over the last three or four blocks of trials; consequently proportions computed over the last 384 trials will be used as estimates of asymptotic performance.

Tables 1, 2, and 3 present the observed values of the probability of an A_1 response over roughly the last 384 trials to the individual stimuli and also to the stimulus compounds. Specifically what is presented is the proportion of A_1 responses to the individual stimuli for the last 100 presentations of each stimulus; similarly, the proportions for the stimulus compounds are based on the last 25 presentations of each stimulus compound.

For all groups the reinforcement schedules are the same for the s_1 and s_2 stimuli, and this similarity is reflected in the observed mean values of p_1 and p_2 given in Tables 1, 2 and 3. There are no significant differences among the three groups on the p_1 measure ($\underline{F} = .05$ with 2 and 45 degrees of freedom) or the p_2 measure ($\underline{F} = .24$). In contrast, the differences among the three groups on the p_3 measure are highly significant ($\underline{F} = 37.72$) reflecting the effect of the π_3 variable.

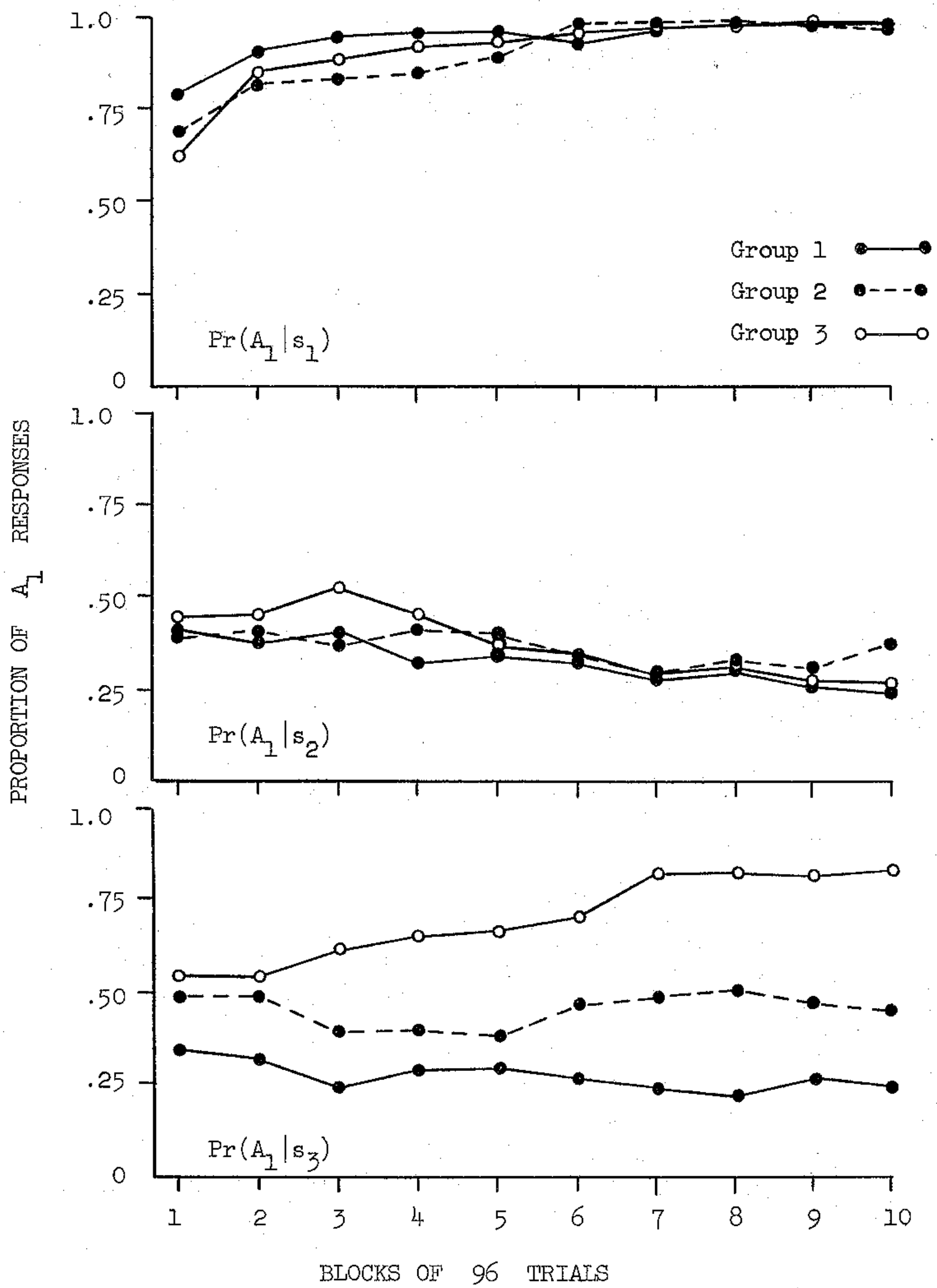

Figure 1. Proportion of A_1 responses on s_i trials.

Subject	p_1	p_2	p_3	p_{12}	p_{13}	p_{23}	p_{123}	S(I)	S(II)	S(III)	ω(I)	ω(II)	ω(III)
1	1.00	.52	.20	.84	.64	.32	.60	.047	.027	.084	1.000	.996	.280
2	1.00	.07	.23	.72	.80	0	.52	.152	.084	.148	1.000	1.000	.440
3	1.00	.16	.14	.60	.60	.28	.52	.042	.006	.057	.629	.628	.200
4	.99	.08	.04	.56	.56	.24	.48	.037	.009	.071	.591	.589	.122
5	.97	.47	.25	.72	.64	.40	.60	.027	.003	.036	1.000	.739	.298
6	.99	.45	.08	.68	.56	.40	.44	.047	.039	.072	.818	.546	.123
7	.97	.37	.52	.56	.52	.56	.72	.080	.076	.069	.082	.235	.128
8	.99	.52	.19	.84	.64	.32	.60	.051	.022	.083	1.000	1.000	.286
9	1.00	.26	.57	.68	.76	.44	.64	.030	.008	.037	.913	.716	.360
10	.98	.18	.67	.68	1.00	.40	.76	.113	.056	.098	1.000	1.000	.541
11	.97	.21	.08	1.00	1.00	.12	1.00	.373	.313	.033	1.000	1.000	1.000
12	.99	.46	.25	.72	.64	.40	.60	.025	.004	.037	.978	.690	.286
13	.97	.25	.03	.68	.24	.08	.20	.152	.169	.290	1.000	1.000	.001
14	.97	.15	.44	.52	.52	.48	.52	.008	.006	.001	.098	.093	.043
15	1.00	.11	.04	.72	.68	.08	.48	.105	.042	.124	.988	.983	.360
16	.96	.31	.27	.60	.56	.44	.56	.033	.017	.018	.521	.315	.131
Average	.98	.29	.25	.69	.65	.31	.58	.082	.055	.079	.789	.721	.287

Table 1. Observed proportions for individual subjects in Group 1.

Subject	p_1	p_2	p_3	p_{12}	p_{13}	p_{23}	p_{123}	S(I)	S(II)	S(III)	ω(I)	ω(II)	ω(III)
1	.97	.34	.48	.68	.72	.44	.64	.025	.006	.020	.978	.746	.383
2	1.00	.43	.54	.80	.84	.92	.68	.153	.123	.156	1.000	.981	.600
3	1.00	.26	.41	.72	.80	.32	.88	.131	.062	.049	1.000	.989	.600
4	1.00	.53	.45	.40	.28	.24	.36	.180	.180	.180	.001	.001	.001
5	.99	.10	.95	.88	1.00	.60	.92	.170	.148	.141	1.000	1.000	.857
6	.97	.63	.49	.60	.56	.52	.60	.013	.014	.016	.333	.277	.213
7	.93	.34	.56	.92	.68	.52	.52	.110	.108	.122	.735	.599	.418
8	1.00	.34	.52	.68	.72	.48	.60	.019	.017	.039	.846	.647	.360
9	.99	.17	.09	1.00	.88	.36	.16	.286	.274	.239	.379	.383	.775
10	1.00	.01	.45	.60	1.00	.12	.56	.138	.069	.181	1.000	1.000	.200
11	1.00	.91	.75	1.00	.92	.80	.92	.038	.012	.043	1.000	1.000	.840
12	.92	.30	.39	.48	.72	.24	.60	.091	.077	.113	1.000	.942	.238
13	1.00	.35	.62	.16	.48	.60	.84	.200	.200	.200	.001	.001	.001
14	.99	.19	.43	.60	.72	.40	.56	.033	.018	.049	1.000	.534	.204
15	.99	.30	.22	.52	.52	.32	.44	.051	.057	.063	.191	.086	.041
16	1.00	.07	.48	.64	.72	.32	.56	.045	.017	.055	.916	.674	.280
Average	.98	.33	.49	.67	.72	.45	.61	.105	.086	.104	.711	.616	.376

Table 2. Observed proportions for individual subjects in Group 2.

Subject	p_1	p_2	p_3	p_{12}	p_{13}	p_{23}	p_{123}	S(I)	S(II)	S(III)	ω(I)	ω(II)	ω(III)
1	1.00	.11	.89	.68	.92	.64	.76	.093	.052	.076	.944	.924	.520
2	1.00	.56	.86	.88	.84	.76	.68	.079	.070	.054	.791	.767	.680
3	1.00	.08	.97	.72	.88	.40	.76	.106	.081	.126	.784	.780	.520
4	.99	.30	.97	.64	.76	.60	.68	.031	.005	.048	.710	.561	.367
5	.99	.30	.42	.44	.36	.36	.36	.120	.120	.120	.001	.001	.001
6	1.00	.03	.97	.60	.84	.36	.92	.133	.110	.195	.701	.698	.680
7	1.00	.14	.95	.56	.72	.56	.60	.019	.015	.048	.463	.459	.200
8	1.00	.14	.95	.60	.72	.76	.60	.079	.066	.073	.463	.459	.200
9	1.00	.52	.68	.84	.88	.56	.72	.043	.030	.056	1.000	.996	.680
10	.97	.60	.96	.80	.88	.84	.72	.060	.047	.052	.817	.816	.639
11	.94	.38	.69	.76	.52	.56	.72	.118	.091	.069	1.000	.988	.500
12	.96	.37	.89	.84	.84	.84	.24	.224	.212	.163	.800	.790	.739
13	1.00	.42	.49	.56	.56	.48	.52	.008	.010	.013	.245	.181	.120
14	.96	.24	.75	.56	.60	.52	.52	.019	.016	.023	.282	.265	.130
15	.98	.15	.94	.76	.58	.28	.52	.123	.122	.133	.174	.173	.166
16	.99	.39	.91	.72	.80	.56	.72	.044	.027	.051	.667	.657	.449
Average	.99	.30	.83	.68	.73	.57	.63	.081	.067	.081	.615	.595	.412

Table 3. Observed proportions for individual subjects in Group 3.

Theoretical analyses. -- We now turn to the problem of predicting the compound probabilities p_{12}, p_{13}, p_{23} and p_{123} in terms of p_1, p_2, and p_3. As indicated earlier, we assume (for all three models) that there may be a regression effect associated with the introduction of a stimulus compound. This regression effect is defined with regard to the parameter ω, and we must estimate ω separately under the assumptions of each model. The estimate of ω was made for individual subjects by a method that is equivalent to a least-squares procedure. Specifically, let $p_{ij}(\omega;I)$ be the prediction for stimulus compound (s_i+s_j) generated by Model I as a function of ω; e.g.,

$$p_{12}(\omega;I) = \omega\left[\frac{1}{2}(\hat{p}_1+\hat{p}_2)\right] + (1-\omega)\frac{1}{2}$$

where $\hat{p}_1$ and $\hat{p}_2$ denote the observed proportions for a particular subject. Then for each subject we define the function

$$S(\omega;I) = \frac{1}{4}\{|p_{12}(\omega;I) - \hat{p}_{12}| + |p_{13}(\omega;I) - \hat{p}_{13}|$$

$$+ |p_{23}(\omega;I) - \hat{p}_{23}| + |p_{123}(\omega;I) - \hat{p}_{123}|\}$$

where the $\hat{p}_{ij}$'s are the observed proportions for the subject. The quantity $S(\omega;I)$ gives the average absolute difference between the predicted and observed values as a function of ω. For each subject an ω was selected that minimized the function $S(\omega,I)$; this was done by computing the function for $\omega = .001\ k$ $(k = 0 \text{ to } 1000)$ and selecting the ω that gave the minimum value. The minimum value of the function is denoted $S(I)$ and the value of ω associated with the minimum is called $\omega(\mathrm{I})$. Using precisely the same methods, we obtain $S(\mathrm{II})$, $\omega(\mathrm{II})$, $S(\mathrm{III})$ and $\omega(\mathrm{III})$ for each subject under the assumptions of Models II and III respectively.

Individual estimates of ω and the corresponding minimum value of $S(\cdot)$ are given in Tables 1, 2 and 3. For a particular subject one can select the model that provides the best fit; i.e., the model that gives the smallest average absolute deviation. For example, Subject 1 in Group 1 has the values $S(\mathrm{I}) = .04$, $S(\mathrm{II}) = .03$, and $S(\mathrm{III}) = .08$; for this subject Model II gives the best fit, Model I is next best and Model III provides the poorest fit. If the information presented in Tables 1, 2 and 3 is tabulated in this fashion, then for Group 1 the best fit is given by Model II in 12 cases, by Model III in three cases, and by Model I in one case. For Group 2, the best fit is given by Model II in 9 cases, Model III in three cases, and Model I in four cases. For Group 3, Model II is best in 11 cases, Model III in three cases, and Model I in two cases. Combining results for all three groups, Model II gives the best fit in 32 cases, Model III in 9, and Model in I in 7.

Possibly a better comparison is provided by considering the three models pairwise on $S(\cdot)$ for individual subjects; i.e., comparing Models I and II, then Models II and III, and finally Models I and III. Again these comparisons can be made by inspecting Tables 1, 2 and 3. Table 4 presents the results of such an analysis. As we see, Model II is better than Model I in 41 of the 48 cases and Model II is better than Model III in 32 of the 48 cases. In terms of these tabulations Model II is clearly the best predictor among the three models.

Table 4

Pairwise comparisons of the three models on the minimum of $S(\cdot)$.

	Models I & II		Models I & III		Models II & III	
	I	II	I	III	II	III
Group 1	1	15	10	6	13	3
Group 2	4	12	12	4	13	3
Group 3	2	14	10	6	13	3
Totals	7	41	32	16	39	9

Table 5 presents the average of the observed p_{ij}'s and also the theoretical values for the three models. Predicted values for each subject were computed (using the estimates of ω given in Tables 1-3) and the averages of these values are presented in Table 5. An inspection of Table 5 suggests that Model II provides the best account of our data, but even for this model some sizable descrepancies exist between observed and predicted probabilities. To obtain a direct measure of the overall goodness-of-fit one can look at the values of S(I), S(II) and S(III) given in Tables 1-3. An average over all 48 subjects yields the following values: $\overline{S(I)} = .089$, $\overline{S(II)} = .069$ and $\overline{S(III)} = .088$. Here again, the statistic favors Model II and indicates that the absolute difference between predicted and observed quantities over all subjects was on the average about .07.

In evaluating the fit of Model II, we also are interested in the estimates of ω. In formulating any of the models considered in this paper, one would assume that ω is determined by the general characteristics of the experimental situation. However, although ω may vary from subject to subject, nevertheless it should be independent of the particular reinforcement schedules employed. Thus, for the present study, one would predict no differences in the mean values of ω over the three groups. By inspecting Tables 1-3 we note that the average value of ω for Model II was .721, .616 and .595 for Groups 1, 2 and 3, respectively. An $\underline{F}$-test on these three groups of ω estimates yields a value of .68 that does not approach significance with 2 and 45 degrees of freedom.

Table 5

Observed and predicted proportions for Models I, II and III.

Group	Model	p_{12}	p_{13}	p_{23}	p_{123}
1	I	.61	.58	.31	.50
	II	.66	.63	.31	.55
	III	.64	.64	.40	.64
	Ob	.69	.65	.31	.58
2	I	.60	.68	.44	.57
	II	.64	.70	.44	.61
	III	.68	.68	.43	.68
	Ob	.67	.72	.45	.61
3	I	.59	.76	.56	.64
	II	.64	.76	.57	.67
	III	.70	.70	.65	.70
	Ob	.68	.73	.57	.63

In terms of the above considerations it appears that Model II provides the best fit to our data and that the regression effect characterized by the parameter ω is relatively constant over different reinforcement schedules. Unfortunately, even for Model II there are some fairly large decrepancies between theory and observation. Thus it seems that other models for stimulus compounding need to be examined and it is for this reason that we have presented our observed results for individual subjects. It is our hope that these data may prove useful in testing new models.

SUMMARY

An experiment on stimulus compounding was conducted using fifth and sixth grade students as subjects. On each of a series of 960 discrete trials, the subject was presented with one of three stimuli, s_1, s_2, or s_3, or with a compound of these stimuli, (s_1+s_2), (s_1+s_3), (s_2+s_3) or $(s_1+s_2+s_3)$. The subject responded to each stimulus presentation by selecting one of two response keys, A_1 or A_2. If π_i is the probability that A_1 is reinforced when s_i is presented then $\pi_1 = 1$ and $\pi_2 = \frac{1}{3}$ for all subjects. Three experimental groups were differentiated by π_3 which took the values $\frac{1}{4}$, $\frac{1}{2}$ and $\frac{3}{4}$. No reinforcement event followed the presentation of a compound. Three models are described that generate predictions for response probabilities to a compound stimulus in terms of response probabilities to the component stimuli. Model I postulates a simple averaging rule. Model II assumes that the influence of each component stimulus is proportional to the likelihood that it elicits a correct response. Model III assumes that the response to the compound is determined solely by the one component that is most frequently reinforced. It was found that Model II gave the best account of the data.

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