

The Effects of Irrelevant Stimuli: 1. The Time Course of Stimulus–Stimulus and Stimulus–Response Consistency Effects With Stroop-Like Stimuli, Simon-Like Tasks, and Their Factorial Combinations

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The effects of Simon- and Stroop-like stimuli are examined in isolation and in factorial combinations with different delays between the presentation of the irrelevant and the relevant stimuli. The effects of irrelevant stimuli have different time courses depending on whether they overlap with the relevant stimulus (stimulus–stimulus overlap, Dimensional Overlap [DO] Type 4) or with the response (stimulus–response overlap, DO Type 3). A new, computational, parallel distributed processing (PDP)–type model, DO'97, is presented that is based on the original DO model (S. Kornblum, 1994; S. Kornblum, T. Hasbroucq, & A. Osman, 1990), and it postulates a nonmonotone irrelevant stimulus activation function in addition to 2 temporally ordered, serial, nonindependent stages: a stimulus processing stage and a response production stage. DO'97 is able to simulate the temporal dynamic characteristics of the processes, with good fits to the empirical data of this study and other published studies, at the level of means, variances, and distributional plots.

After decades of empirical, and generally fragmented, research on stimulus–stimulus (S–S) and stimulus–response (S–R) compatibility effects, attempts have recently been made to understand the broad theoretical underpinnings of this large class of phenomena. Some of these attempts, instead of treating each effect in isolation, as had been done in the past, have tried to identify the processing principles that they have in common. Thus, by carefully examining these effects, particularly the effects of irrelevant stimuli, many similarities have become apparent. For example, when the irrelevant aspects of a stimulus are consistent with the relevant aspects either of the stimulus or of the response, reaction times (RTs) tend to be faster than when they are inconsistent (for reviews see Hommel & Prinz, 1997, and Proctor & Reeve, 1990).¹ Different combinations of such consistency relationships produce the so-called Stroop effect (for a review see MacLeod, 1991), the Simon effect (for a review see Simon, 1990), and other compatibility effects.

The dimensional overlap (DO) model (Kornblum, Hasbroucq, & Osman, 1990; Kornblum & Lee, 1995) postulates a single processing structure and ascribes these various consistency effects to different processes, or combination of processes, within this structure depending on whether the irrelevant stimulus is consistent or inconsistent with the relevant stimulus (S–S) or with the response (S–R). Hommel (1993) has also shown that in addition to the particular nature of the dimensional overlap (S–S or S–R overlap), the temporal relations between the various processes are an important determinant of performance. In this study we pursued these leads by examining the time course and the resulting temporal interactions of S–S and S–R processes empirically and theoretically for DO Types 3, 4, and 7 (see Kornblum & Lee, 1995, for the latest version of the DO taxonomy).² In a subsequent article (Kornblum, 1999) we

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¹ “Relevant” attributes have a correlation of 1 with the responses; “irrelevant” attributes have a correlation of 0. In addition, subjects are instructed to pay attention to the relevant attributes and to ignore the irrelevant ones.

² Dimensional overlap is the degree to which relevant and/or irrelevant stimulus sets are perceptually, conceptually, or structurally similar to the response set in the task and/or to each other. Even though similarity, hence DO, is a continuously varying quantity, when it is used as a criterion variable in the construction of the DO taxonomy, it is treated discretely. All combinations of these three potential sets in a task, each with one of two binary values, generates eight potential task types that constitute the eight types in the DO taxonomy (see Appendix). Of particular interest in the present study are DO Types 3, 4, and 7. DO Type 3 is a task in which the sets of irrelevant stimuli and responses are the only ones with dimensions that overlap; DO Type 4 is a task in which the sets of irrelevant and relevant stimuli are the only ones with dimensions

Table 1
 Values for the Experimental Conditions That Differed
 Between Experiments 1 and 2

Experiment	Warning interval (ms)	SOA (ms)	Intertrial interval
1	400–600	0, 50, 100, 200	600–1,200 ms
2	600–1,200	0, 100, 200, 400, 800	2–3.5 s

Note. SOA = stimulus onset asynchrony.

will examine the time course of S-S and S-R consistency effects in other DO-type tasks.

Two methods have generally been used to vary the temporal relationship between internal processes: (a) The external events purported to trigger these internal processes have been staggered in time (the stimulus onset asynchrony [SOA] method), thus priming one of the processes and giving it a head start (e.g., Glaser & Glaser, 1982; Posner & Snyder, 1975; Taylor, 1975); and (b) the duration of one of the internal processes was lengthened by varying its difficulty. The latter can be done either by increasing the discrimination difficulty (e.g., Miller, 1982) or by degrading the stimuli (e.g., Sternberg, 1969). In the present study we used the SOA procedure.

Some studies in the literature, using the SOA procedure, have already suggested that S-S and S-R consistency effects exhibit different time courses. For example, Kornblum (1994), using a two-choice, left–right, keypressing task, with color as the relevant stimulus dimension, found that the S-R consistency effect (i.e., the difference in RT between S-R consistent and S-R inconsistent trials) is larger when the relevant and irrelevant stimuli are presented simultaneously than when they are separated by a 200-ms delay. This decrease in the magnitude of the S-R consistency effect with SOA is consistent with findings by De Jong, Liang, and Lauber (1994) and Lu (1994/1995). In contrast, the S-S consistency effect increases at a 200-ms delay (Kornblum, 1994).

Because the two experiments that we report have many methodological characteristics in common, they are described in the General Method section. The few procedural differences are specified with each experiment and are summarized in Table 1.

General Method

Stimuli and Responses

The responses consisted of left and right keypresses made with the index fingers of the left and right hands. The stimuli consisted of a rectangle 1.5 cm × 3.3 cm, which, viewed from a distance of 75 cm, subtended a visual angle of 2.5°. Three attributes were varied within this rectangle: color, position, and word. Color was the relevant attribute; position and word were both irrelevant (see Footnote 1). The color was either blue or green. “Position” refers to the particular half of the rectangle in which the color was

that overlap; and DO Type 7 is a combination of Types 3 and 4 (see Figure 1).

presented. That is, a line bisected the rectangle into either a left and right half, or a top and a bottom half. The color was then presented in one of these halves. Because the left–right split overlapped with the left–right responses, left–right color stimuli on any one trial were either consistent or inconsistent with the responses (S-R consistency). Up–down stimuli were neutral with respect to the responses. “Word” refers to a word that was presented in the middle of the rectangle. The word, in Experiment 1, was either *blue*, *green*, *detail*, or *novel*. (In Experiment 2, the words were in French: *bleu* for “blue,” *vert* for “green,” and *note* and *date* for the two neutral words.) The first two words overlapped with the relevant stimuli (color) and were, therefore, either consistent or inconsistent with it (S-S consistency); the last two words did not overlap with either the relevant stimuli or the responses and were, therefore, neutral with respect to both. Thus, position and word either overlapped or did not overlap with the response and relevant stimulus, respectively. These combinations of relevant and irrelevant attributes generated the 32 different experimental stimuli that were used in this study (see Figure 1). The stimuli during training consisted of solid green or blue stimulus rectangles. In Experiment

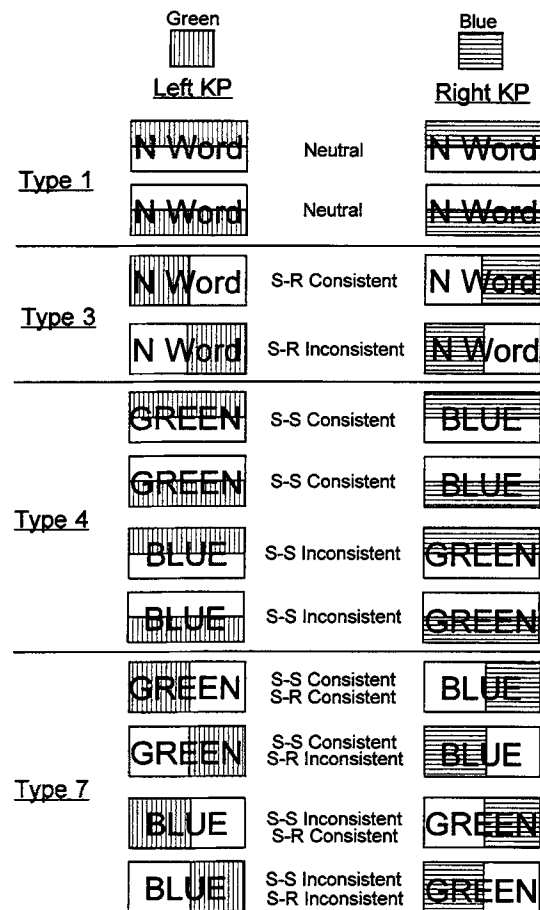


Figure 1. The relevant stimuli were the colors blue and green, here represented as vertical and horizontal striations respectively. For labeling purposes, we assumed that the color green was mapped onto the left keypress (KP) and the color blue onto the right keypress; during the experiments, this assignment was balanced across subjects. There were two neutral (N) words: *detail* and *novel*. Thirty-two stimuli are therefore represented in this figure. S-R = stimulus–response; S-S = stimulus–stimulus.

1, there was a string of four Xs in the middle where a word would otherwise have appeared; in Experiment 2, the entire rectangle was filled with color.

The rectangle in which the stimuli appeared was defined by a white border 1 pixel wide. The two halves of the rectangle, whether horizontal or vertical, were also separated by a white line 1 pixel wide. The words were written in white capital letters edged by a black line 1 pixel wide. The CRT screen on which the stimulus rectangle appeared was black, as was the uncolored half of the rectangle.

Trial Events

Each trial began with a fixation pattern consisting of the four corners of the stimulus rectangle; simultaneously with the onset of the fixation pattern, there was a 50-ms, 1-Khz warning tone. Following a randomly chosen warning interval (whose duration differed for Experiments 1 and 2; see Table 1), the rectangle that had been outlined by the four corners was completed, and either just the two irrelevant attributes (word and position) or all three attributes (color, word, and position) were presented inside the rectangle. In the zero-delay condition, all three attributes were presented at the end of the warning interval. However, when the delay was nonzero (delay durations differed between experiments; see Table 1), only the irrelevant aspects of the stimulus (word and/or position) were presented at this time; position was indicated by filling the appropriate half of the rectangle in gray. The color blue or green then replaced this gray, after a delay. Following the presentation of the color, the stimulus was either response terminated (Experiment 1), or it stayed on the screen for 1 s (Experiment 2); this was followed by feedback, which stayed on the screen for 1.5 s. After a randomly chosen intertrial interval (for which the range of durations differed between experiments; see Table 1), the warning signal for the next trial was presented.

Experiment 1

The purpose of this experiment was to investigate the time course of the S-R and S-S consistency effects (Types 3 and 4) in isolation and in a relatively narrow window of time.

Method

Subjects. The 12 subjects who participated in the experiment were all students at the University of Michigan who had volunteered in response to an ad in the student newspaper. They were all right-handed men and native English speakers, with no visual, auditory, or motor handicaps, and they were paid for their participation in the experiment. They were each run for a total of 12 experimental blocks in addition to 1 training block.

Stimuli, procedure, and conditions. The stimuli consisted of those labeled as *Type 1* (neutral), *Type 3* (S-R overlap), and *Type 4* (S-S overlap) in Figure 1. There were four delay conditions (0, 50, 100, and 200 ms). Each stimulus type was presented in a separate block, with a particular delay, and the eight individual stimuli within each type were randomly presented within that block. All four delays were run with the same stimulus type before switching over to another stimulus type. The order of stimulus types was counterbalanced across subjects, and the order of delays within stimulus type was randomized in accordance with a Latin square.

Each experimental block consisted of 64 trials and was preceded by 8 warm-up trials that were excluded from the analysis. Subjects received a 1-min rest between Trials 32 and 33 and between blocks.

Results

Separate analyses of variance (ANOVAs) were performed for the S-R overlap (Type 3), the S-S overlap (Type 4), and the neutral (Type 1) conditions. Delay had a significant main effect for the S-S overlap, $F(3, 33) = 5.85, p < .0025$, and the neutral conditions, $F(3, 33) = 3.99, p < .0157$; there was no significant main effect of delay for S-R overlap, $F(3, 33) = 0.17, p > .9$. Consistency had a significant main effect for both the S-R overlap, $F(1, 11) = 19.84, p < .0010$, and the S-S overlap, $F(1, 11) = 35.16, p < .0001$, conditions. The Consistency \times Delay interaction was highly significant for the S-S condition, $F(3, 33) = 18.25, p < .0001$, and barely significant for the S-R condition, $F(3, 33) = 2.6, p < .0690$. There was a significant Delay \times Response interaction (left-right) for the S-S condition, $F(3, 33) = 5.86, p < .0025$. We also analyzed consistency effects with overlap (S-S/S-R) and delay as factors. Neither delay, $F(3, 33) = 2.44, p < .0817$, nor overlap, $F(3, 33) = 2.05, p < .1799$, had a significant effect; however, the Delay \times Overlap interaction was highly significant, $F(3, 33) = 18.86, p < .0001$. No other effects were statistically significant at this level of analysis.

In order to investigate the interaction of consistency with delay more closely (see top portion of Table 2), we performed separate analyses at each delay for the S-S and S-R conditions. For the S-R conditions, consistency had a significant effect at 0 ms (34 ms), $F(1, 11) = 43, p < .0001$, 50 ms (40 ms), $F(1, 11) = 13.88, p < .0033$, and 100 ms (34 ms), $F(1, 11) = 16.4, p < .0019$; it ceased to be significant at 200 ms (15 ms), $F(1, 11) = 2.04, p = .18$. This pattern was reversed for the S-S condition. Here, consistency had no significant effect either at 0 ms (2 ms), $F(1, 11) = 0.86, p = .3744$, or at 50 ms (2 ms), $F(1, 11) = 0.08, p = .7797$. However, it started being significant at 100 ms (29 ms), $F(1, 11) = 17.99, p < .0014$, and became even more significant at 200 ms (53 ms), $F(1, 11) = 39.12, p < .0001$.

Discussion

The trends in the time course of the S-S and S-R consistency effects in this experiment are consistent with those reported for a similar experiment (Kornblum, 1994) in which only two delays were used (0 and 200 ms), and the data fill in the gaps in SOA values that existed in that experiment. That is, the S-R consistency effect appears to decrease with delay, whereas the S-S consistency effect appears to increase.³ Even though both trends may be

³ Tom Carr and an anonymous reviewer pointed out that what we took to be a difference in the time course of S-S and S-R consistency effects may in fact be a difference between the time course of location and identity processing because of a confounding in our experiments between these two sets of variables. Although this is logically possible, it is unlikely to be the case. In another experiment from our laboratory (see Experiment 3 in Zhang, 1994/1995), in which words were the irrelevant stimuli in both Type 3 (S-R overlap) and Type 4 (S-S overlap) tasks, the time courses of the S-S and S-R consistency effects were different and shared important characteristics with the time course differences found in the present experiments.

Table 2
*Empirical and Simulated Reaction Times (RTs), Standard Deviations,
 and Consistency Effects for Experiment 1*

Overlap	SOA	Consistent (c)			Inconsistent (i)			Effect
		RT	SD	% error	RT	SD	% error	i-c
Empirical data								
S-R (Type 3)	0	386	59	1.6	420	75	9.6	34
	50	380	66	2.6	420	65	6.3	40
	100	382	71	1.6	416	61	8.6	34
	200	393	67	2.8	408	60	3.9	15
S-S (Type 4)	0	378	55	4.7	380	51	3.9	2
	50	374	57	6.8	376	56	5.5	2
	100	374	59	4.2	403	74	9.1	29
	200	374	67	2.3	427	72	9.4	53
Neutral (Type 1)	0	375	58	3.1				
	50	375	58	4.8				
	100	370	56	5.3				
	200	392	59	3.9				
Simulated data								
S-R (Type 3)	0	383	42		417	46		34
	50	384	52		420	48		36
	100	384	53		416	46		32
	200	388	56		411	43		23
S-S (Type 4)	0	372	60		382	57		10
	50	374	60		386	61		12
	100	374	61		394	72		20
	200	373	63		425	75		52

Note. Stimulus onset asynchrony (SOA), RTs, SDs, and consistency effects are expressed in milliseconds. S-R = stimulus-response; S-S = stimulus-stimulus; i = inconsistent; c = consistent.

described by a monotone function—increasing for the S-S and decreasing for the S-R conditions, respectively—note that the S-R consistency effect appears to increase slightly between 0 ms and 50 ms before decreasing. This and the other trends in the data are examined in greater detail with a distributional analysis (see Figure 2).

A distributional analysis (see De Jong et al., 1994; Ratcliff, 1979; Zhang & Kornblum, 1997) is a two-step process. First the data are “Vincentized” and averaged over subjects, and then RT differences between corresponding quantiles of these averaged distributions are calculated. That is, one first constructs the RT distributions of S-R (or S-S) consistent trials and S-R (or S-S) inconsistent trials for each subject. Each of these distributions is then partitioned into N quantiles, or proportional bins, such that each bin contains the same proportion ($1/N$) of trials; this permits one to calculate the mean RT per quantile, or bin, across subjects, for the consistent and the inconsistent distributions. The difference between the consistent and the inconsistent mean RTs of corresponding bins in these two distributions is the magnitude of the consistency effect at the mean RT of the bins that were used to calculate these differences. The results of such distributional analyses, based on quintiles, are plotted in Figure 2 for the S-R and S-S conditions, respectively.

The mean RT data (see top portion of Table 2) suggested that the magnitude of the S-R consistency effect rose and then fell between 0 and 100 ms. The distributional analyses confirmed this suggestion in greater detail. The size of the

S-R consistency effect increased monotonically at delays of 0 and 50 ms. At 100 ms it appeared to start out as an increasing function but quickly turned into a decreasing one, and at 200 ms it decreased with no turnarounds. In contrast, the S-S condition showed no increase for the first two delays (0 and 50 ms) but a steep monotone rise at delays of 100 and 200 ms. These distributional analyses complement the results obtained with mean RTs and support the observation of an initial rise in the S-R consistency effect at short delays, as well as the conclusion that the effects of irrelevant stimuli follow different time courses depending on whether they overlap with the relevant stimuli (S-S overlap) or with the responses (S-R overlap).

Experiment 2

The principal purpose of the second experiment was to extend the number as well as the range of delays in order to obtain a more complete picture of the time course of these S-S and S-R consistency effects. In addition, because a previous study (Kornblum, 1994) had suggested that S-S and S-R consistency effects were additive, and that study had only two delays (0 and 200 ms), we wanted in particular to examine the additivity of these S-S and S-R effects at other SOA values.

Method

Subjects. Subjects were 20 volunteers who were recruited by the Center for Research in Cognitive Neurosciences at the CNRS in

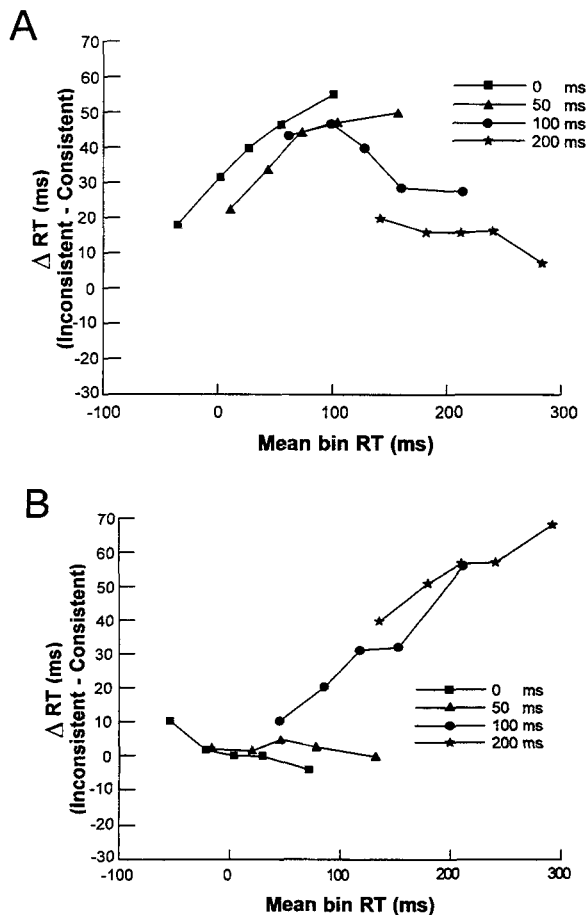


Figure 2. Distributional plots for the (A) Type 3 (S-R overlap) and (B) Type 4 (S-S overlap) conditions in Experiment 1. The abscissa in this and all other distributional plots consists of the difference between the neutral mean reaction time (RT) and the overall mean RT for the consistent and inconsistent conditions. This sometimes causes the mean bin RT to be negative. (See also Footnote 8.)

Marseille, France. Half the subjects were men and half were women; their ages ranged between 19 and 25 years. Two of the men were left-handed; the remaining subjects were right-handed. All subjects were native French speakers with no visual, auditory, or motor handicaps.

Procedure and conditions. Given the dual purpose of this experiment, the stimuli were either Type 7, which includes irrelevant S-S and S-R overlap (see Figure 1), or Type 1, which are neutral. All conditions were run in blocks of 96 trials, split into two subblocks of 48 trials each. There was a 1-min rest between the two subblocks of a condition, as well as between different conditions. The first subblock of any new condition was always preceded by 16 warm-up trials.

The five delays (0, 100, 200, 400, and 800 ms) constituted five blocked experimental conditions. Within each delay condition, one third of the trials (32) were neutral (n) with respect to both the relevant stimuli and the responses; the other two thirds overlapped with both the stimuli and the responses. Of these, one sixth (16) were doubly consistent (c/c), that is, S-S and S-R consistent; one sixth were doubly inconsistent (i/i), that is, S-S and S-R inconsis-

tent; one sixth were S-S consistent and S-R inconsistent (c/i); and the remaining sixth were S-S inconsistent and S-R consistent (i/c). (See Figure 1 for the exact stimuli included in each condition.)

The experiment lasted 2 hr.⁴

Design. Of the 20 subjects, half were run with one mapping of colors to keys, half with the other mapping. All subjects began their experimental session with a training block. Following the training block, they were run on the five delay conditions, which had been arranged in a Latin square. There were two different Latin squares per mapping condition.

Results

The first ANOVA analyzed the effects of four factors: S-S/S-R consistency, delay, and mapping.⁵ Delay had a highly significant effect, $F(4, 68) = 22.52, p < .0001$, as did S-S consistency, $F(1, 17) = 36.86, p < .0001$, and S-R consistency, $F(1, 17) = 56.74, p < .0001$. S-S and S-R consistency each interacted with delay: S-S, $F(4, 64) = 6.45, p < .0002$; S-R, $F(4, 68) = 10.23, p < .0001$. S-S and S-R consistency also interacted with each other, albeit marginally, $F(1, 17) = 4.28, p < .0542$. Mapping had no significant effect, $F(1, 17) = 0.01, p > .9$, and was dropped from all subsequent analyses.

The second ANOVA found a highly significant effect of delay with neutral stimuli, $F(4, 68) = 13.63, p < .0001$.

In order to examine the interactions of S-S and S-R consistency with delay, we subtracted the neutral RT from each of the four RTs at each delay (see Figure 3A) and performed a third ANOVA on these differences, with S-S/S-R consistency and delay as the factors.

Here, delay ceased to have a significant main effect, $F(4, 68) = 0.79, p > .5326$. However, its interactions with S-S and S-R consistency remained unchanged and were still significant beyond the .0002 level. This was equally true of the S-S \times S-R interaction, which remained unchanged and marginal at slightly above the .05 level.

The effects of S-S and S-R consistency were further examined in a fourth set of ANOVAs, in which these effects were examined at each delay separately. The S-R consistency effects were significant beyond the .005 level at all delays except at Delay 200 (14 ms), $F(1, 18) = 5.2, p < .035$, and Delay 400 (7 ms), $F(1, 18) = 4.4, p < .0503$. The S-S effects were significant beyond the .007 level at all delays except zero, where the S-S effect was not statistically significant at all, $F(1, 18) = 0.64, p < .4350$. The only delay at which the S-S and S-R effects interacted was at Delay 100, $F(1, 18) = 5.17, p < .0355$.

Discussion

The main effect (in the ANOVA sense) of delay in this experiment was an overall decrease in mean RT as delay

⁴ The first 45 min were used to place electroencephalogram electrodes on the subjects' scalps. Some of the results of this experiment have previously been reported in Kornblum and Requin (1995) and in Stevens, Whipple, Requin, and Kornblum (1996).

⁵ The data for 1 subject at one delay were missing from the record; all the analyses were therefore based on 19 subjects.

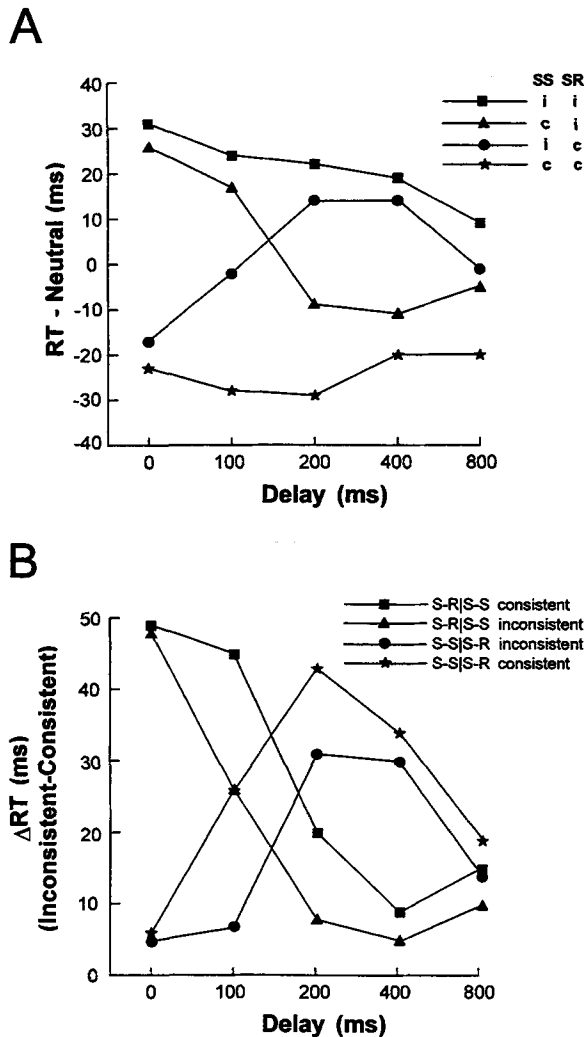


Figure 3. A: Mean reaction time (RT) differences (RT - neutral) for the four experimental conditions in Experiment 2, plotted on a log scale as a function of delay stimulus onset asynchrony [SOA]. B: Given the factorial combination of stimulus-stimulus (S-S) and stimulus-response (S-R) consistency conditions, each of the four marginal differences in the resulting 2×2 table was a consistency effect, either S-S or S-R, conditionalized on the consistency condition of the other. On the ordinate are these mean S-S and S-R consistency effects for the four experimental conditions in Experiment 2, plotted on a log scale as a function of delay (SOA). i = inconsistent; c = consistent.

increased. This is evident from the fact that the delay factor was highly significant in the first ANOVA, in which the data consisted of the raw RTs for the experimental conditions; it was highly significant in the second ANOVA, in which the data were the raw RTs for the neutral condition only; and it ceased to be significant in the third ANOVA, in which the data consisted of the differences in RT between the neutral and the experimental conditions. This subtraction appears to have eliminated the main effect of delay. However, the interaction of delay with S-S and S-R consistency remains untouched by this subtraction, and this, of course, is its most

interesting and theoretically significant effect, because this interaction reflects the time course of the S-S and the S-R consistency effects. The details of this interaction are evident in Figure 3.

The RTs for the doubly consistent (c/c) and the doubly inconsistent (i/i) conditions were the fastest and slowest, respectively, at all delays (see Table 3 and Figure 3A).⁶ The results for the mixed consistency conditions, c/i and i/c, were more complex. At zero delay they were indistinguishable from the doubly consistent (c/c) and doubly inconsistent (i/i) conditions in which the S-R consistency values matched their own. That is, the mixed c/i condition, in which S-S was consistent and S-R inconsistent, did not differ significantly from the doubly inconsistent (i/i) condition; similarly, the mixed i/c condition, in which S-S was inconsistent and S-R consistent, did not differ significantly from the doubly consistent (c/c) condition. As delay increased, the RTs for the mixed conditions left the doubly consistent/inconsistent (c/c-i/i) condition that matched their own S-R consistency values and approached the doubly consistent/inconsistent (c/c-i/i) conditions that matched their S-S consistency values instead. It is as if the overall RT at long delays was primarily determined by S-S consistency, just as at short delays it was determined by S-R consistency, with a mixture of influences in between. This pattern of results—the interaction of S-S and S-R consistency with delay—makes it clear that S-S and S-R consistency effects follow different time courses, which is made more evident in Figure 3B, in which the S-S and S-R consistency effects themselves are plotted as a function of delay.

Here we see two major patterns: one reflecting the S-S effects, the other the S-R effects. The S-S effects have an inverted U-shape, whereas the S-R effects appear to be monotone-decreasing functions. That is, S-S consistency has no effect at zero delay. However, as delay increases, so does the effect of S-S consistency until, after approximately 200 ms, it decreases again. S-R consistency, however, is strongest at extremely short delays and then decreases throughout the range of larger delays used in this experiment. Note that both the S-S and the S-R consistency effects appear to be slightly different depending on the consistency value of the other variable. That is, when S-R is consistent, the S-S consistency effects are slightly different (as shown by the pair of almost parallel curves) than when S-R is inconsistent. The same is true of the S-R consistency effects. Even though these differences are small, and only marginally significant, we take the consistency of these patterns as strong evidence for the fact that the effects of S-S and S-R overlap interact

⁶ The irrelevant stimulus word, unless it was neutral and did not overlap with either the relevant stimulus or the response, was either consistent (c) or inconsistent (i) with the relevant stimulus (color), thus generating two values of S-S consistency. Similarly, the irrelevant stimulus position, unless it was neutral, was either consistent (c) or inconsistent (i) with the response, which generated two values of S-R consistency. All the overlapping stimuli, therefore, fit into a 2×2 table. We use the convention of specifying the value of S-S consistency first, followed by the value of S-R consistency (e.g., c/i, for S-S consistent and S-R inconsistent, etc.).

Table 3
Empirical Reactions Times, Standard Deviations, and Error Rates (% Error) for Experiment 2

Overlap		Delay (ms)														
		0			100			200			400			800		
S-S	S-R	M	SD	% error	M	SD	% error	M	SD	% error	M	SD	% error	M	SD	% error
c	c	366	63	0.8	352	81	3.8	355	69	1.6	333	60	1.2	328	58	0.4
c	i	415	80	5.5	397	67	7.5	375	64	2.8	342	59	2.3	343	58	2.6
i	c	372	71	3.0	378	81	2.5	398	71	5.3	367	68	3.2	347	68	1.7
i	i	420	88	5.5	404	68	11.2	406	73	7.3	372	62	6.0	357	62	2.9
Neutral		389	67	2.3	380	71	3.0	384	66	1.5	353	59	0.8	348	63	1.9

Note. S-S = stimulus-stimulus; S-R = stimulus-response; c = consistent; i = inconsistent.

and are not additive (in the additive factors sense; see Sternberg, 1969), as we had previously thought. However, as we are to show, this interaction does not necessarily imply that the stimulus and response stages are no longer serial, as we have assumed in the DO model. We postpone a detailed discussion of this issue, and of the mechanism underlying this interaction, until after the presentation of our computa-

tional model. However, before turning to the model, we present in Figure 4 a distributional plot of these data.

As was true of the distributional analyses of Experiment 1, the S-R effect at zero delay has a positive slope, which strengthens our conjecture that the S-R consistency effect increases for a very short time before decreasing (see also Figure 3 in Zhang & Kornblum, 1997). This, together with

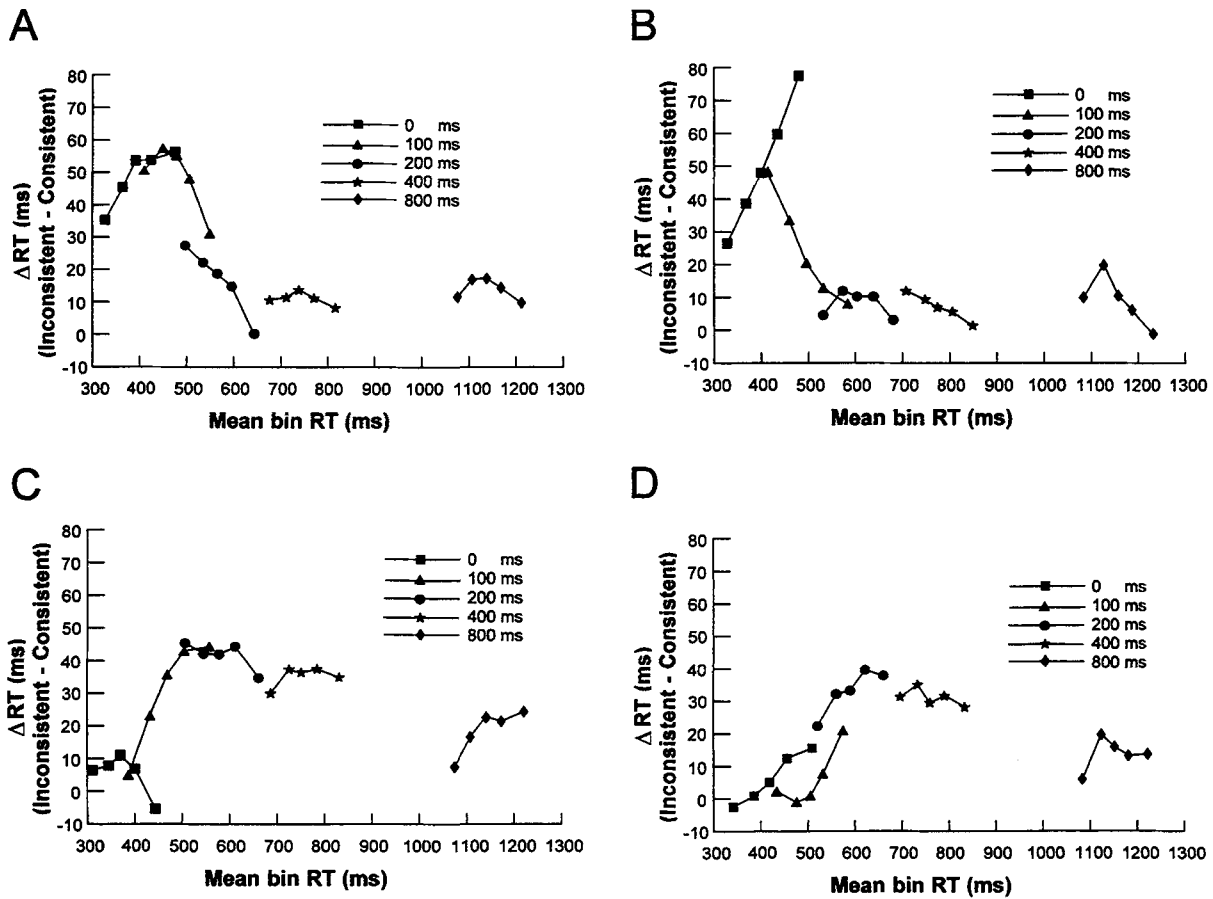


Figure 4. Distributional plots for the four experimental conditions of Experiment 2. A: Stimulus-response (S-R) consistency effect, with stimulus-stimulus (S-S) consistent. B: S-R consistency effect, with S-S inconsistent. C: S-S consistency effect, with S-R consistent. D: S-S consistency effect, with S-R inconsistent. (See also Footnote 8.) RT = reaction time.

the suggestion of inverted U-shapes for the distributional plots at the 100-ms-delay conditions (for both Experiments 1 and 2), strengthens our conjecture that following its brief period of increase, the S-R consistency effect decreases precipitously and flattens out roughly at the point at which the mean bin RT is 600 ms. This is in remarkably close agreement with similar observations by Hommel (1997) and is in sharp contrast to the S-S effects that rise before they fall (and that perhaps would have fallen even further had we included longer SOA values in the experiment).

In the next section we present a parallel distributed processing (PDP) network that incorporates some modifications of the original DO model and appears to capture the temporal dynamics of the processes underlying the empirical findings of these two experiments.

A Computational Model

The ultimate goal of the network model that we have been developing is to account for the effects of DO, S-R mapping, S-S and S-R consistency, and temporal dynamics in all eight types of tasks included in the DO taxonomy (Kornblum, 1992; Kornblum et al., 1990).⁷ Thus, our model—DO'97—is intended to be quite general and has an architecture that can be adapted to simulate a wide variety of tasks. It differs from other, similar models in two important respects: First, as was true in the original DO model (Kornblum et al., 1990), the present model assumes that processing is divided into two distinct, sequential stages (*stimulus processing* and *response production*); second, it assumes a rising and falling automatic activation curve that interacts with controlled processes in producing a response. This second assumption is an important modification of the processing mechanism found in earlier versions of the DO model (Kornblum, 1992; Kornblum et al., 1990; Kornblum & Lee, 1995) and has some similarities to Hommel's (1993) temporal overlap hypothesis; however, as we shall see, it differs in fundamental ways from it. These two assumptions are critical for understanding the time course of these different compatibility phenomena, for together they give rise to the temporal dynamics characteristically associated with S-S and S-R overlap.

The Network Architecture

As is generally true of PDP models (e.g., McClelland, 1993; Rumelhart, Hinton, & McClelland, 1986), processing in our model takes place in a system of connected modules that are organized into layers, where each module consists of a set of elementary processing units. As is also true of other PDP models that deal with S-S and S-R compatibility effects (e.g., Cohen & Huston, 1994; Cohen, Dunbar, & McClelland, 1990; Cohen, Servan-Schreiber, & McClelland, 1992; Phaf, van der Heijden, & Hudson, 1990; Zhang, 1994/1995; Zorzi & Umiltà, 1995), these modules represent dimensions—or mutually exclusive classes of features—of either stimulus properties (when the modules are in the input layer) or response properties (when the modules are in the output layer). The activation of a unit within a module, therefore,

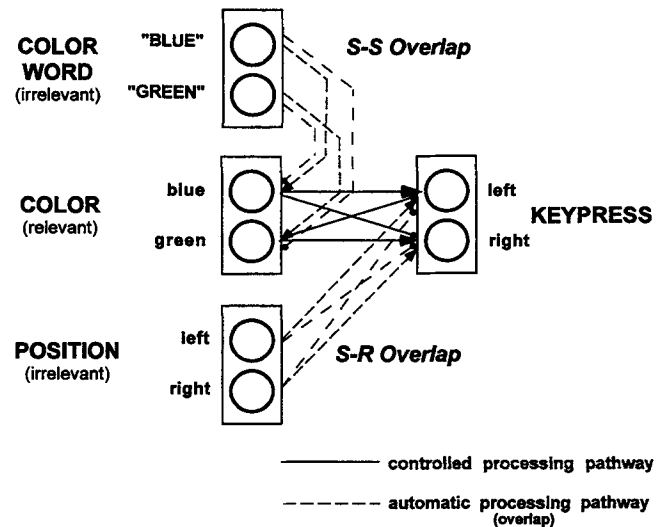


Figure 5. Architecture of the model. S-S = stimulus–stimulus; S-R = stimulus–response.

represents the activation of a feature (either stimulus or response) along that dimension.

Module structure and representation. Our model consists of two layers: an input layer and an output layer. There are also four kinds of modules representing different potential aspects of an experimental task (see Figure 5). The input layer consists of at least one module, representing the relevant stimulus dimension in the task. Similarly, the output layer consists of at least one module, representing the relevant response dimension in the task. In addition to these two modules, each layer may contain additional modules corresponding either to irrelevant stimulus dimensions (in the input layer) or to irrelevant response dimensions (in the output layer). In this way the model can easily accommodate the wide variety of tasks represented in the DO taxonomy. In this article, however, we restrict our discussion to those modules (dimensions) that are required to simulate the empirical results from the first two experiments reported here (DO Types 3, 4, and 7).

Thus, for present purposes, the relevant stimulus module represents the color of the stimulus, and the relevant response module represents the set of keypress responses. In addition to these, there are two irrelevant stimulus modules: one representing color word, the other representing stimulus position. The structure and information-processing machinery within each of the different kinds of stimulus modules are identical. Relevant and irrelevant stimulus dimensions are distinguished solely by the preexperimental instructions that define the task and determine the units' inputs and connectivity.

Automatic processing and dimensional overlap. Modules that represent task dimensions that overlap are connected with "automatic processing lines," and the strength

⁷ A working version of the model may be found at <http://www.umich.edu/~kornblum>.

of these connections (δ) is proportional to the degree of DO between them. Thus, when the relevant and irrelevant stimulus dimensions overlap (i.e., when there is S-S overlap, as, for example, in Types 4 and 7), there are automatic connections between the two stimulus modules in the input layer. When there is overlap between the irrelevant stimulus and the response (i.e., when there is S-R overlap, as, for example, in Types 3 and 7), there are automatic connections between the irrelevant stimulus module in the input layer and the response module.

Following models proposed by Cohen et al. (1992) and Phaf et al. (1990), the automatic processing pathways consist of positive (excitatory) connections between the "corresponding" units of each module and negative (inhibitory) connections between the "noncorresponding" units of each module. Thus, when the irrelevant stimulus dimension is stimulus location (left-right) and the relevant response dimension is response location (left-right), excitatory automatic lines connect the *left* stimulus unit with the *left* response unit, and the *right* stimulus unit with the *right* response unit. Furthermore, inhibitory automatic lines also connect the *left* stimulus unit with the *right* response unit, and the *right* stimulus unit with the *left* response unit. Note that the inhibitory activity is between, and not within, modules.

This pattern of connectivity ultimately enables the model to account for both facilitation effects (via the excitatory effect of coactivation of compatible features) and interference effects (via the inhibitory effect of coactivation of incompatible features). Some models have accounted for interference effects by having inhibitory connections between units of the same module, thus forcing units within each module to "compete" for activation (e.g., Cohen et al., 1992; Grossberg, 1976; McClelland, 1993; McClelland & Rumelhart, 1981; Zorzi & Umiltà, 1995); other models have incorporated both intra- and intermodule inhibition (e.g., Phaf et al., 1990; Zhang, 1994/1995). Our decision to have inhibitory lines between noncorresponding units of different modules, rather than among units within each module, is motivated by sheer model simplicity. Little theoretical or empirical evidence exists to motivate a preference for one over the other (e.g., see Mordkoff, 1995), and no solid convention appears to have been agreed upon in the literature.

Controlled processing and stagelike dynamics. In addition to the automatic lines, there is a set of controlled processing lines that connect the relevant stimulus module to the response module according to the mapping instructions. These connections represent a controlled "decision" process associated with stimulus identification. To implement this, DO'97 has a feature that does not appear in previous models of S-S and S-R compatibility: Thresholds exist at both the input and the output layers rather than at the output layer only, as is generally the case (e.g., Cohen et al., 1990; McClelland, 1993; Zhang, 1994/1995). Whenever activation in a relevant stimulus unit reaches the stimulus threshold, a discrete *on* signal (a constant positive value) is sent down the controlled line from that unit to the appropriate response unit (specified by the mapping). The moment a stimulus unit first

reaches threshold and initiates controlled activation of a response can be considered the end of *stimulus-stage* processing, just as the moment a response unit reaches threshold can be considered the end of *response-stage* processing. It should also be noted that if more than one relevant stimulus unit reaches threshold during processing—if, for example, an incorrect unit reaches threshold because of S-S DO and processing variability—each of these units will initiate its associated response through its own controlled line.

Another mechanism that divides processing into stagelike stimulus and response components is that, until some unit in the input layer reaches the *stimulus threshold* (the threshold for the output of the input layer), the activation of the units in the response module are "clamped to zero" (see Hinton & Sejnowski, 1986, pp. 289–290, on this terminology), and no processing is allowed to take place in the response module. As a result, automatic processes due to S-R DO cannot influence the response units until the stimulus threshold has been reached.

This unique feature gives our network the characteristics that make it similar to serial stage models of RT. For example, in our model any RT can be decomposed into a *stimulus-processing stage*—the time from the onset of the stimulus to the time when activation in one of the units in the input layer reaches threshold—and a *response-production stage*—the time from the beginning of response processing (i.e., when the stimulus threshold is reached) to the time when activation in one of the units in the response module reaches threshold. These two quantities are then added together to produce the overall RT.

Activation and information flow. In almost all PDP models designed to simulate RT phenomena (e.g., Cohen et al., 1990; McClelland, 1993; Zhang, 1994/1995; Zorzi & Umiltà, 1995), the individual processing units are "feature detectors" in which activation gradually accumulates over time. With a few notable exceptions (e.g., Phaf et al., 1990), this is usually accomplished by using an activation function similar to that first used by McClelland (1979) in his cascade model; we have followed this practice.

Thus, at time t , units take as their net input the weighted sum of the outputs of units connected to it,

$$\text{net}_j(t) = \sum_i o_i(t)w_{ij}, \quad (1)$$

where $o_i(t)$ is the output at time t of each unit from which unit j receives input, and w_{ij} is the weight (or strength) of the connection from unit i to unit j . The activation of a unit is simply a running average of its net input over time,

$$a_j(t) = \alpha \text{net}_j(t) + (1 - \alpha)a_j(t - 1), \quad (2)$$

where $\text{net}_j(t)$ is the net input to unit j at time t and α is a rate constant. This time-averaging function establishes the time course of processing in the model. One feature of this function is that when the input to the unit is fixed, the activation gradually climbs through time and asymptotically approaches a value equal to the input (McClelland, 1979).

To produce the output of the unit, the activation is passed

through a logistic function. This introduces nonlinearity into the model, giving the network a variety of desirable characteristics (see Cohen et al., 1990, for discussion). The output function is calculated by

$$o_j(t) = \frac{1}{1 + e^{\kappa(1/2 - a(t))}}, \quad (3)$$

where $a(t)$ is the activation of the node for which the output is being calculated at time t , and κ controls the degree of nonlinearity of the function.

Conceptually, the flow of information can be described as follows: When the stimulus is first presented, activation begins to accumulate in units of the input layer that correspond to features in the stimulus. To the degree that there is S-S overlap, the activation of different units, corresponding to different stimulus features, may interact with one another—producing either facilitation or interference. Whenever a relevant stimulus unit's activation level reaches the stimulus threshold, it triggers a controlled process that initiates the accumulation of activation in a response unit. Until the first controlled signal is sent down the controlled lines, the response units are clamped to zero, and automatic activation from units in the stimulus layer cannot influence response activation. Signals sent through the controlled lines lead to an accumulation of activation in the response units. With S-R overlap, activation of the irrelevant stimulus unit leads to the automatic activation of the corresponding response unit, which interacts with the accumulation of activation in one of the response units due to the controlled lines. This interaction is either facilitative (in the case of S-R consistency) or interfering (in the case of S-R inconsistency), and it continues until the activation level in a response unit reaches the response threshold, and a response (presumably the correct response) is chosen. This competitive activation process cum threshold in the response layer can be interpreted as implementing a combined verification and abort stage, as postulated in the original DO model (Korblum et al., 1990).

Because of the manner in which the relevant and irrelevant stimulus information interact along the automatic pathways, S-S overlap will only directly influence the duration of the stimulus-processing stage (the processing that occurs before the stimulus threshold is reached), and S-R overlap will only directly influence the duration of the response-processing stage (processing that occurs after the stimulus threshold is reached). This leads to the important result that the processing effects of S-S and S-R overlap are separated in time and implies that the effects of S-S and S-R overlap follow different time courses. However, in order to understand this aspect of the network's dynamics, we must consider the time course of the irrelevant stimulus activation function.

Irrelevant stimulus activation. We postulate that the inputs to both the relevant and the irrelevant stimulus units start at the same value (set at 1 for the simulations). The input to the relevant unit remains at that value, whereas input to the irrelevant unit decays at a fixed rate (ρ) shortly

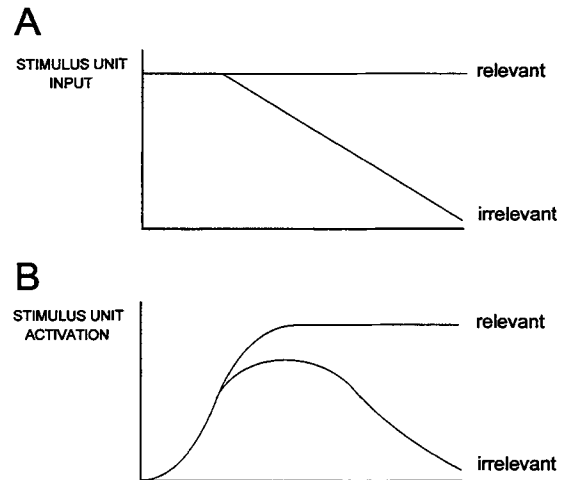


Figure 6. A: Input to the relevant and the irrelevant stimulus units, shown as a function of time. B: Activation functions in the relevant and the irrelevant stimulus units, shown as a function of time.

following its onset (see Figure 6A). In accordance with Equation 2, these inputs cause the activation levels in both the relevant and the irrelevant stimulus units to increase—at first. However, as the input to the irrelevant stimulus unit starts to decay, the activation level in that unit levels off and starts to decrease, whereas the activation level of the relevant unit continues to increase until it reaches threshold at time t (see Figure 6B). These input and stimulus activation assumptions are similar to, but differ in important respects from, those used by Zorzi and Umiltà (1995). First, Zorzi and Umiltà had no stimulus threshold. Second, apparently influenced by Hommel's (1993, 1994) studies, Zorzi and Umiltà had the activation (instead of the input) of the irrelevant stimulus start out at the same constant value as the relevant stimulus and subsequently decay over time. By distinguishing between the inputs to the stimulus units and the resulting activation functions in those units, our model is able, quite naturally, to generate an activation function for the irrelevant stimulus that is a nonmonotone, inverted, U-shaped function. Zorzi and Umiltà, however, had an irrelevant stimulus activation function that starts at a maximum and then decays. This difference, as we shall see, is of central importance.

Automatic activation of the irrelevant stimulus affects performance by altering the rate at which activation builds up (see Equation 2) for the relevant stimulus (in the case of S-S overlap) and for the response (in the case of S-R overlap). Hence, S-S and S-R overlap alter the time required for activation in either the relevant stimulus or the response units to reach their respective thresholds. In particular, when the irrelevant stimulus is consistent with the relevant stimulus (S-S consistent) or with the response (S-R consistent), activation in the appropriate unit grows at a faster than normal rate, thus reaching threshold sooner; when the irrelevant stimulus is inconsistent (S-S or S-R inconsistent), activation grows at a slower than normal rate, thus reaching

threshold later. Furthermore, because, in the case of S-R overlap, the irrelevant stimulus cannot exert its influence on the response unit until after the stimulus-processing stage has been completed (recall that the response units are clamped to zero until after completion of stimulus processing), this influence involves a later point on the activation curve of the irrelevant stimulus than in the case of S-S overlap. This has important consequences for the time course of S-S and S-R consistency effects.

The effects of activation asynchrony. When activation in the irrelevant stimulus unit starts before activation in the relevant stimulus unit has begun, for example, when the irrelevant stimulus is presented before the relevant stimulus (SOA), it effectively means that the entire automatic activation curve for the irrelevant stimulus has been shifted to an earlier point in time (see Figures 6B and 7) and has a head start on the activation of both the relevant stimulus unit and, necessarily, of the response. Because the effects of S-S and S-R overlap are mediated by separate, temporally ordered stages of processing, the effects of such activation asynchrony have differential consequences depending on whether the overlap of the irrelevant stimulus is with the relevant stimulus (S-S overlap) or with the response (S-R overlap). If the overlap is with the relevant stimulus (S-S overlap), the effect of S-S overlap (consistency and inconsistency) as a function of SOA increases at first and then decreases, roughly following the shape of the irrelevant stimulus

activation function. If, however, the irrelevant stimulus overlaps with the response (S-R overlap), this interaction occurs during the response-processing stage (i.e., later during the processing sequence than the interaction caused by S-S overlap), when the irrelevant stimulus activation function may have already passed its peak. As a result, there is only a very short time during which increasing the SOA would result in an increase in the effect of the irrelevant stimulus before the effect begins to decrease—or, as is often observed, there may not be any increase at all (e.g., De Jong et al., 1994), and the effect of irrelevant S-R overlap simply decreases monotonically with increasing SOA.

Processing variability. The final specification of the model is the introduction of processing variability. Human performance is inherently variable. Reaction time data thus come as distributions. In order to capture this variability, we introduced randomness into the model by adding gamma-distributed noise to the net input of each unit on each trial (cf. Cohen et al., 1990), as well as to the output of the response unit. We also attempted to capture individual differences between subjects by adding normally distributed noise to the threshold values and to the degree of dimensional overlap for each subject.

Automatic activation of the incorrect (congruent) response. According to the model's automatic response activation hypothesis, whenever the irrelevant stimulus overlaps with the response, the response that is congruent

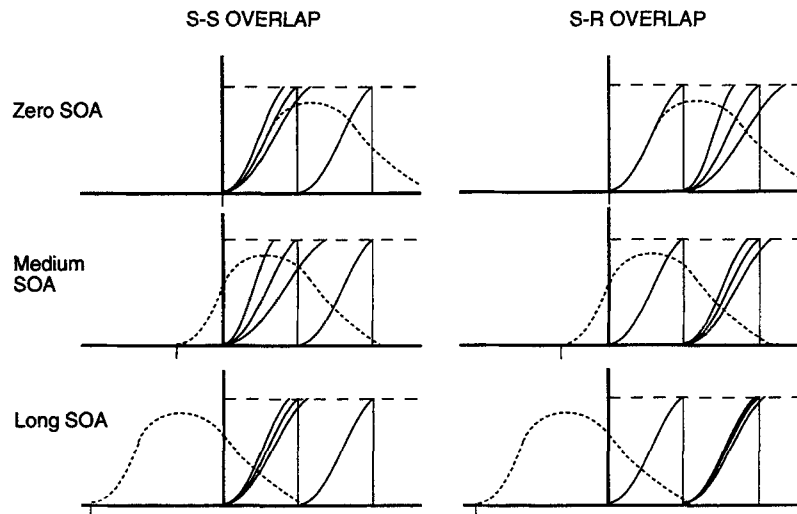


Figure 7. The effects of stimulus onset asynchrony (SOA) on model dynamics. On the left are shown the effects of an irrelevant stimulus with stimulus–stimulus (S-S) overlap; on the right are the effects of an irrelevant stimulus with stimulus–response (S-R) overlap. SOA increases from top to bottom. The horizontal long-dashed lines represent thresholds for the stimulus (left) and response (right) stages. The short-dashed, inverted U-shaped line represents the activation function of the irrelevant stimulus, which shifts to the left as SOA increases; tick marks on the horizontal axis indicate the onset of the irrelevant stimulus. The “ordinate” represents the strength of activation and marks the point in time when the relevant stimulus is presented. The other two vertical lines on each graph mark the point in time when the relevant stimulus (the first line) and the response (the second line) activation levels have reached threshold in the absence of any enhancement or degradation by the irrelevant stimulus (i.e., neutral). The two lines straddling the neutral activation functions represent the enhanced (accelerated in the case of consistent relationships) and degraded (slowed in the case of inconsistent relationships) activation functions.

with that stimulus is automatically activated. Thus, during S-R inconsistent trials, two responses are activated simultaneously: the congruent, and erroneous, response, and the correct, S-R inconsistent, response. The congruent response is automatically activated because of its positive automatic connection with the irrelevant stimulus. The input to that response unit is $\delta\sigma_i(t)$, that is, the same input as that of a correct S-R consistent response unit (see Equation 8) but without the constant input from the controlled line. Because the input to this incorrect automatic response unit is proportional to the irrelevant stimulus activation curve, the activation level in this unit follows a nonmonotone function that rises slightly before falling again because of the decrease in activation of the irrelevant stimulus. Figure 8A shows this incorrect response activation, along with the activation of the correct response and the irrelevant stimulus, during the response stage for an S-R inconsistent trial.

Although activation of the incorrect response is difficult to measure empirically, the activation curve postulated by the model is consistent with the findings from a number of studies that have used tasks with S-R DO and inferred the presence of automatic incorrect response activation either from (a) error analyses (e.g., Kornblum & Zhang, 1991), (b) lateral readiness potential (LRP) data that were assumed to represent response activation, or (c) other event-related potential (ERP) results (see, e.g., Leuthold, 1994; Osman,

Bashore, Coles, Donchin, & Meyer, 1992; Smulders, 1993; Valle-Inclan, 1996; Wascher & Wauschkuhn, 1996). Moreover, the shape of the LRP (which is a difference curve; see Coles, 1989) for S-R inconsistent trials obtained in studies that have used Type 3 (Simon) tasks closely resembles the difference curve between the correct and incorrect response unit activation predicted by the DO'97 model (see Figure 8B). In particular, both curves initially dip "below zero" (toward the incorrect, automatically activated response) before climbing toward activation of the correct response. Even though in many cases it would be consistent with the DO'97 model to view these neurophysiological data as indices of response activation, there are reasons in other cases to be cautious in unequivocally accepting such an interpretation of the ERP and LRP data. We discuss these reasons in greater detail later (see *The Seriality Assumption* section).

Summary

The architecture of our model is based on the following characteristics:

1. Presentation of a relevant stimulus feature generates a constant input of 1 to the corresponding stimulus unit; presentation of an irrelevant stimulus feature generates an input to the corresponding stimulus unit that is initially 1. However, after some period of time τ , this irrelevant input decreases linearly with a slope ρ . These inputs result in two differently shaped activation functions: the activation function in the relevant stimulus unit, which resembles a logistic function, and that in the irrelevant stimulus unit, which has an inverted U shape.

2. Activation in the input modules rises from the onset of the stimulus until the output of some relevant stimulus unit first reaches the stimulus threshold. This is considered the stimulus-processing stage. During this period, the response module remains inactive. However, if there is S-S overlap, then the two stimulus modules can interact through automatic-processing lines.

3. Whenever a relevant stimulus unit reaches threshold, its associated controlled line begins sending an input value of 1 to the response unit designated by the task. The first time this happens, activation in the irrelevant stimulus module is allowed to start acting on the activation function in the response module via S-R automatic processing lines (if there is S-R overlap). Activation in the response module accumulates until one of the units reaches the response threshold. This period is considered the response-processing stage.

4. Automatic processing connections between modules are excitatory between corresponding, or consistent, units and inhibitory between noncorresponding, or inconsistent, units. The weight of these lines (δ) is proportional to the degree of DO between the dimensions represented by the modules in question. For a given degree of DO, any asymmetry between the net inhibition caused by coactivation of noncorresponding units and the net facilitation caused by coactivation of corresponding units can be taken as a parameter ϕ : the ratio of inhibition to excitation.

5. Reaction time is the total number of time steps between

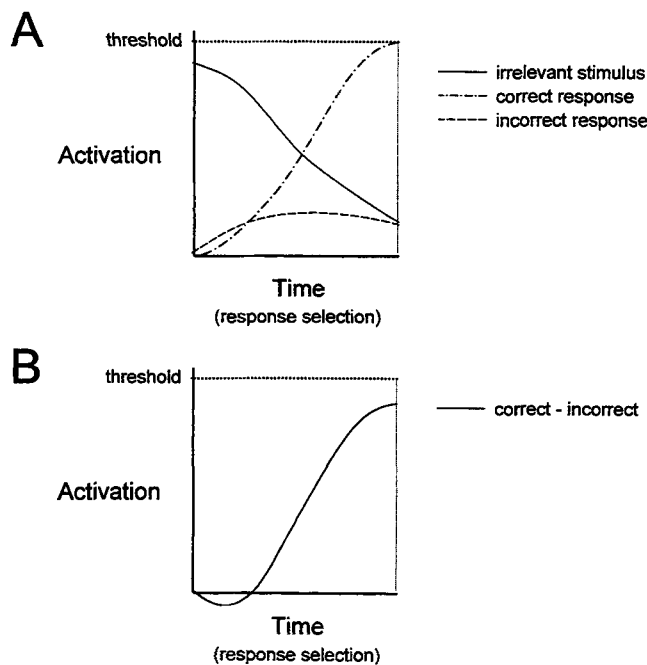


Figure 8. Activation levels in the response stage for a stimulus-response inconsistent trial in a Type 3 (Simon-type) task. A: The activation levels for the irrelevant stimulus, the correct response, and the incorrect (automatically activated congruent) response. B: The difference (correct - incorrect) in the activation levels of the correct and incorrect response units (i.e., the difference in the activation levels of the correct and incorrect responses, as shown in A).

the onset of the stimulus and the point when a unit in the response module reaches the response threshold. Variability in RT is introduced by adding gamma-distributed noise to the net input of each unit.

6. The net input to a unit in each module can therefore be specified. For the relevant stimulus unit, when relevant and irrelevant stimuli are consistent,

$$\text{net}_r(t) = 1 + \delta o_i(t), \quad (4)$$

and when they are inconsistent,

$$\text{net}_r(t) = 1 - \delta \phi o_i(t), \quad (5)$$

where δ is the degree of S-S DO, ϕ is the ratio of DO inhibition (due to inconsistency) to excitation (due to consistency), and $o_i(t)$ is the output of the irrelevant stimulus unit.

For the irrelevant stimulus unit, when relevant and irrelevant stimuli are consistent,

$$\text{net}_i(t) = (1 - \nu\rho) + \delta o_r(t), \quad (6)$$

and when they are inconsistent,

$$\text{net}_i(t) = (1 - \nu\rho) - \delta \phi o_r(t), \quad (7)$$

where ν is equal to zero until time (t) reaches the *attentional delay interval* (described as τ above) and is equal to $(t - \tau)$ after that, and where ρ is equal to the slope of the decrease in input to the irrelevant unit. The output from the relevant stimulus unit is $o_r(t)$.

For the response unit, when irrelevant stimulus and response are consistent,

$$\text{net}_r(t) = 1 + \delta o_i(t), \quad (8)$$

and when they are inconsistent,

$$\text{net}_r(t) = 1 - \delta \phi o_i(t), \quad (9)$$

where the activation begins at zero from when the stimulus threshold is met (as opposed to the onset of the stimulus itself), whereas the output of the irrelevant stimulus unit, $o_i(t)$, is the same output that has been calculated since the initial onset of the stimulus.

Simulations

Because in Experiment 2 we examined the effects of both S-S and S-R overlap for a broad range of SOA values, we simulated the results of Experiment 2 first. The model was, therefore, configured to represent the conditions of Experiment 2, and the parameters were set to provide the closest fit to the empirical data. In order to demonstrate the robustness of the model, we then show that by systematically varying parameters in theoretically appropriate ways, the model is able to simulate the data from Experiment 1, as well as

comparable data from Hommel's (1997) Experiment 2 and De Jong et al.'s (1994) Experiment 3.

Experiment 2

The model architecture (see Figure 5) includes two irrelevant stimulus modules (one representing color word, the other representing position) and one relevant stimulus module (representing stimulus color), as well as one relevant response module (representing keypress). One of the irrelevant stimulus modules (color word) has automatic lines connecting it to the relevant stimulus module (color); the other (position) has automatic lines connecting it to the response module. Controlled lines connect the relevant stimulus module (color) to the response module in accordance with the appropriate mapping (defined by the color-to-key mapping instruction). The value for the excitatory controlled lines (between corresponding relevant S-R pairs) was 1.0; for the excitatory automatic lines (between corresponding S-S and S-R pairs), it was .75. Theoretically, the strength of the automatic lines corresponds to the degree of DO between the dimensions, with the constraint that they have to be between 0 and 1. We chose the value of .75 to represent fairly large DO in the cases of both S-S and S-R overlap. The negative connections (between noncorresponding pairs) in both the controlled and the automatic-processing pathways had a value of one-half the magnitude of the positive connections ($-.5$ for the controlled lines and $-.375$ for the automatic lines), following the convention that between-module inhibition weights are often weaker than excitatory connections (cf. Zhang, 1994/1995; Zorzi & Umiltà, 1995).

The accumulation of activation within each unit is controlled by the parameter α (see Equation 2), which describes the rate at which activation will approach the value of the unit's input. Because the continuous nature of the processes in the model is best approximated with small values of α (Hubbard & West, 1991), for present purposes we set the value of α to .0005. Any small changes in this value would merely scale the simulated results without changing important properties of the simulated data. With this value, activation in the stimulus and response units increases gradually until the respective thresholds (θ_s , θ_r) are reached. These thresholds were both set to .4.

Although we recognize that position information and color-word information are processed at different rates (e.g., Hommel, 1994; Shiu & Kornblum, 1995), we have no theoretical basis at this time for systematically varying the parameters that control the shape of the automatic activation curves—namely, the time delay before (τ), and the rate of (ρ), decrease of input to the irrelevant stimulus. As a result, these parameters were set at identical values for the two irrelevant stimulus modules. The rate of decrease was set to .0005, with a delay of 800 time steps. This allowed the irrelevant stimulus activations to approach the stimulus threshold value without crossing it.

A summary of these parameters and of their values is given in Table 4. In addition to the parameters discussed above, the output function nonlinearity (κ ; see Equation 3)

was set to 20. We set the value of ϵ to 0.5, enabling us to examine the effects of variability on the model. As mentioned before, several of these parameters are robust with respect to the qualitative properties of the model's dynamics and cause only minor changes in the simulation results.

Simulation 1: Mean reaction times and effect sizes. This simulation was run with the parameter values listed in Table 4. Because the model was designed to account for the influences of DO on performance, we did not attempt to simulate the effects of SOA in the neutral condition. In order to compare the empirical results with the simulation, we used the difference RT (RT - neutral) as our empirical data (see Figure 3A) and also subtracted a constant (simulated neutral RT for Type 1) from the simulated RTs for each condition. We then calculated the linear regression of the simulated (RT - neutral) mean values for each condition against the empirical (RT - neutral) mean values for each condition in order to obtain a measure of goodness of fit and an equation for converting simulated time-step units into millisecond units.

The simulated means for each condition are presented in Figure 9, and compared with the empirical means shown in Figure 3, they appear to provide a reasonably good fit. The correlation between the simulated and the empirical means was .9283 ($R^2 = .8617$). The transformation equation converting simulated time-step units into milliseconds was $ms = (.055) \text{ time steps} + 1.00$.

Simulation 2: Distributional analyses. It has been shown that the slope of the distributional plots is determined by the relative magnitude of the variances of the two distributions entering into the plot (see Zhang & Kornblum, 1997). In the discussion of the results from Experiment 1, we also indicated that these slopes provided a finer grained analysis than the means—of the time course of the S-S and S-R effects—and may reflect the shape of the underlying activa-

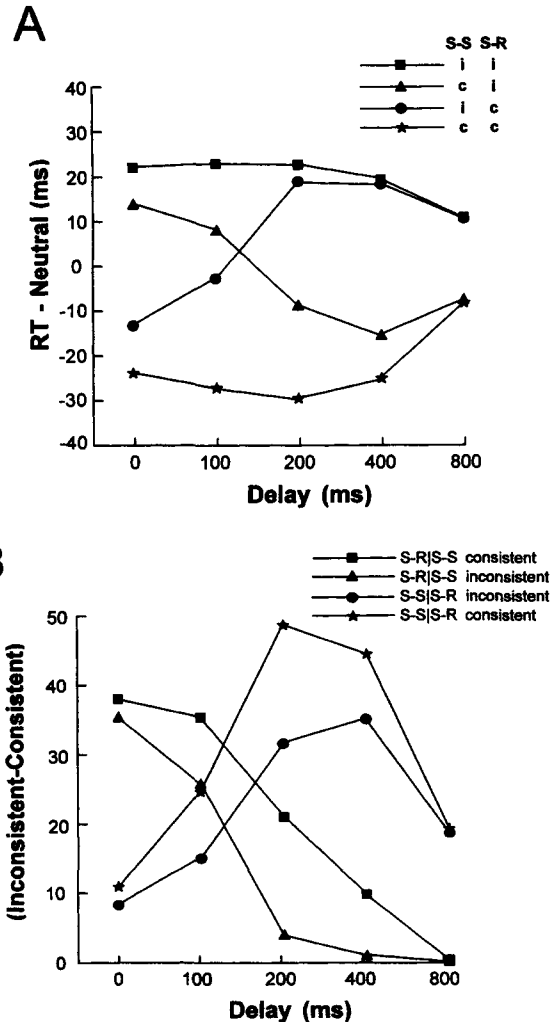


Figure 9. A and B: Simulated results for Experiment 2. The abscissa in this and all other distributional plots consists of the difference between the neutral mean reaction time (RT) and the overall mean RT for the consistent (c) and inconsistent (i) conditions. This sometimes causes the mean bin RT to be negative. (See also Footnote 8.) S-S = stimulus-stimulus; S-R = stimulus-response.

tion function of the irrelevant stimulus. In order to test whether our model had captured this deeper aspect of processing in these tasks, we calculated the distributional plots of the simulated data. These plots, shown in Figure 10, demonstrate patterns remarkably similar to those of the distributional plots of the empirical S-R data shown in Figure 4, which suggests that our model has indeed captured some of the basic characteristics of information processing in these tasks.⁸

⁸ Even though the simulated data consist of (RT - neutral) and the empirical data plotted in Figure 4 include the neutral RT, these data are comparable and differ only by a scaling factor on the abscissa. The neutral RTs included in the empirical plots simply shift the distributional plots at any one delay by the mean neutral RT, which is roughly 400 ms within a 50-ms range over delays.

Table 4

Parameter Values Used for the Simulations of Experiment 2

Parameter	Value	Function
δ	.75	Strength of the automatic processing pathway (proportional to the strength of DO)
ϕ	.50	Ratio of inhibition strength to excitation strength (used as a coefficient for inhibitory line weights)
α	.0005	Rate of accumulation of activation in units
ρ	.0005	Rate of decrease of the irrelevant stimulus input
τ	800	Time delay before irrelevant stimulus input decrease
θ_s, θ_r	.4	Stimulus and response threshold values
κ	20	Degree of output function nonlinearity
$\sigma^2(\epsilon)$.5	Level of noise in the system (where ϵ is a gamma variable added at each time step)

Note. Parameters were changed only slightly for simulations of Experiment 1, Hommel's (1997) Experiment 2, and De Jong et al.'s (1994) Experiment 3 (see text for further details). DO = dimensional overlap.

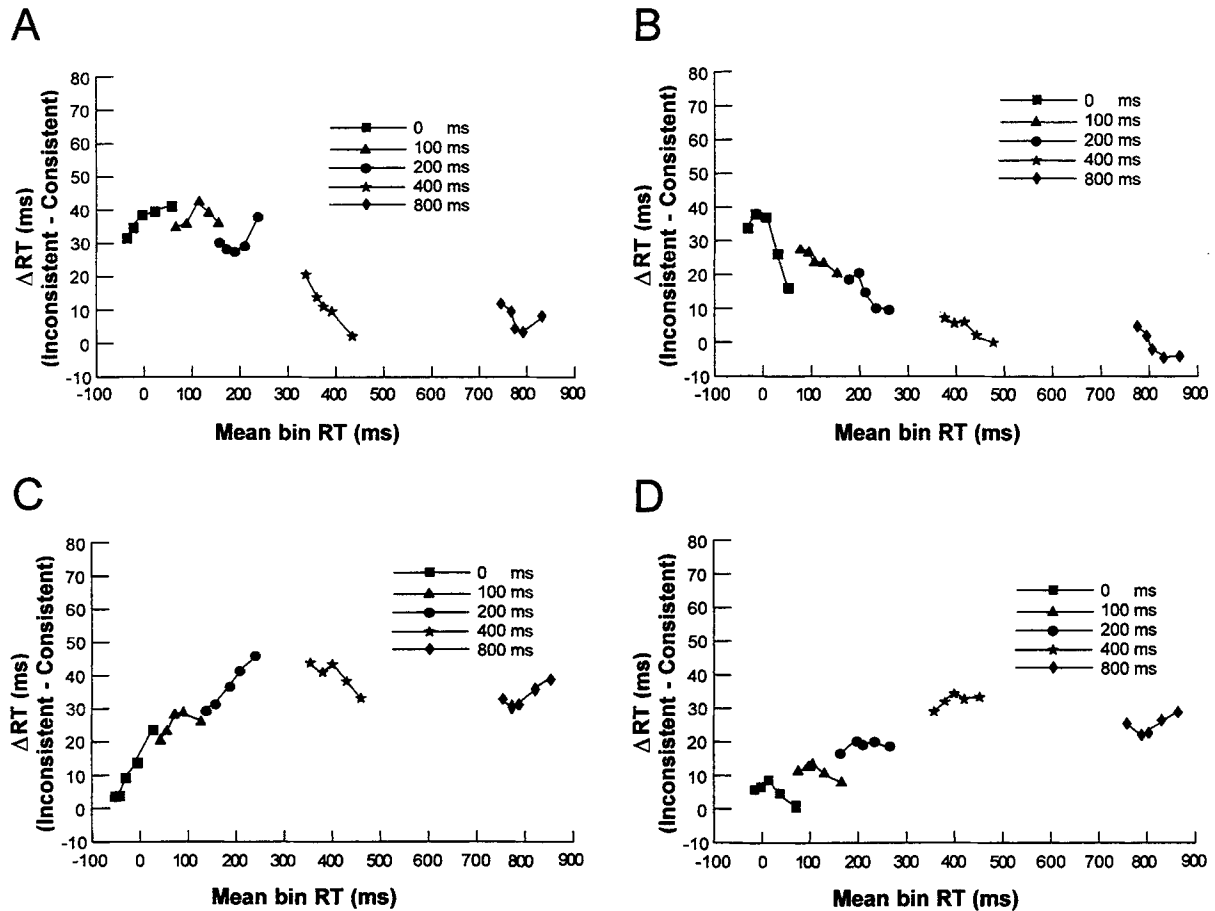


Figure 10. A–D: Distributional plots for simulated data (reaction time [RT] – neutral) in Experiment 2. The abscissa in this and all other distributional plots consists of the difference between the neutral mean RT and the overall mean RT for the consistent and inconsistent conditions. This sometimes causes the mean bin RT to be negative. (See also Footnote 8.)

Experiment 1

Because the stimulus conditions in Experiment 1 were almost identical to those in Experiment 2, the model structure and parameter values for the simulation of Experiment 1 should be identical to those used for Experiment 2, with two exceptions. Recall that the irrelevant stimuli in all the blocks of Experiment 1 overlapped either with the relevant stimulus or with the response, but never with both. That is, the stimuli were either Type 3 or Type 4. The stimuli in Experiment 2, however, were all Type 7, with simultaneous S-S and S-R overlap. This difference led us to make two changes in the model parameters:

1. DO (δ). For these simulations, either the strength of the automatic-processing lines between the two stimulus modules or the strength of the automatic-processing lines between the stimulus and the response modules were set to .75, but not both at the same time. This allowed the model to simulate pure Type 3 and pure Type 4 (pure S-R overlap and pure S-S overlap) conditions.

2. Stimulus and response thresholds (θ_s and θ_r). Because each experimental block contained irrelevant stimulus fea-

tures that overlapped either with the relevant stimulus or with the response, but never with both, these tasks were easier than the task in Experiment 2. Thus, because Experiment 1 had fewer potential sources of interference than Experiment 2, subjects, in principle, would have been able to base their decision on less evidence (or stimulus activation) in Experiment 1 than under the relatively more complex task conditions of Experiment 2. This assumption, that subjects optimize their processing thresholds, is supported by the observation that the RT for neutral trials, when mixed in blocks with simple stimulus conditions (e.g., Type 3 and Type 4), is slightly, but significantly, faster than when neutral trials are mixed in blocks with more complex stimulus conditions (e.g., Type 7; see Kornblum, 1994). We implemented this difference in difficulty between the experiments by changing both the stimulus and the response threshold values from .5 (in the simulation of Experiment 2) to .2.

Simulation 1: Mean reaction times and effect sizes. The second simulation was run with these two new parameter values. Because the Type 3 and Type 4 stimulus conditions

were presented to subjects in different blocks of trials, we performed separate regressions on the mean (RT – neutral) values for each of these conditions to allow for block-by-block variability. As we did for Experiment 2, we used the difference RT (RT – neutral) as our empirical data and subtracted a simulated neutral RT from the simulated RTs for each condition.

Once again, the simulated data, presented in the lower portion of Table 2, appear to provide a reasonably good fit to the empirical data, presented in the upper portion of Table 2. The correlation between the simulated and the empirical data was .9877 ($R^2 = .9756$) for the Type 3 condition and .9460 ($R^2 = .8949$) for the Type 4 condition. The transformation equations converting simulated time-step units into milliseconds were $ms = (.065) \text{ time steps} + 220$ for Type 3 and $ms = (.113) \text{ time steps} + 66$ for Type 4.

Simulation 2: Distributional analyses. As can be seen in the lower portion of Table 2, the behavior of the simulated means matched that of the empirical means fairly closely. The sign of the differences between the variances of the S-R inconsistent and consistent conditions (Type 3) was identical at all SOA values for the simulated and the empirical data, including the sign reversal at an SOA of 200. The simulated and the empirical variances also matched closely in the Type 4 condition. Thus, the simulation seems to have captured important properties of the empirical data, namely, $\sigma(i) > \sigma(c)$ for Type 4 and the reversal from $\sigma(c) < \sigma(i)$ to $\sigma(c) > \sigma(i)$ as a function of SOA for Type 3. These are reflected in the distributional plots shown in Figure 11.

Because Experiments 1 and 2 were so similar, a further test of the generality and robustness of the model was desirable. Both Experiment 2 in Hommel (1997) and Experiment 3 in De Jong et al. (1994) were Type 7 tasks (i.e., they included both S-S and irrelevant S-R DO) that used different stimulus sets from the previous experiments and therefore provided ideal data for testing the generality of the model.

Hommel's (1997) Experiment 2

The task in Hommel's (1997) Experiment 2 consisted of left–right keypresses made to target-letter stimuli that were presented either to the left or to the right of a central fixation point; these target letters were themselves flanked by letters that were either consistent or inconsistent with the target letter. In the DO taxonomy this corresponds to a Type 7 task. Hommel (1997) examined the time course of the S-S and S-R consistency effects by dividing his RT distributions into quintiles. Two important differences may be noted between the stimulus conditions used by Hommel and those used in the two experiments of our present study; these differences correspond to theoretically important differences in the parameter values of our simulations:

1. *Irrelevant stimulus input.* In Hommel's (1997) *horizontal* condition, the flanker letters appeared to the left and right of the target letter; in the *vertical* condition, the flanker letters appeared above and below the target letter. Hommel (1997) argued that retinal resolution is greater for picking up horizontal-position flankers than vertical-position flankers.

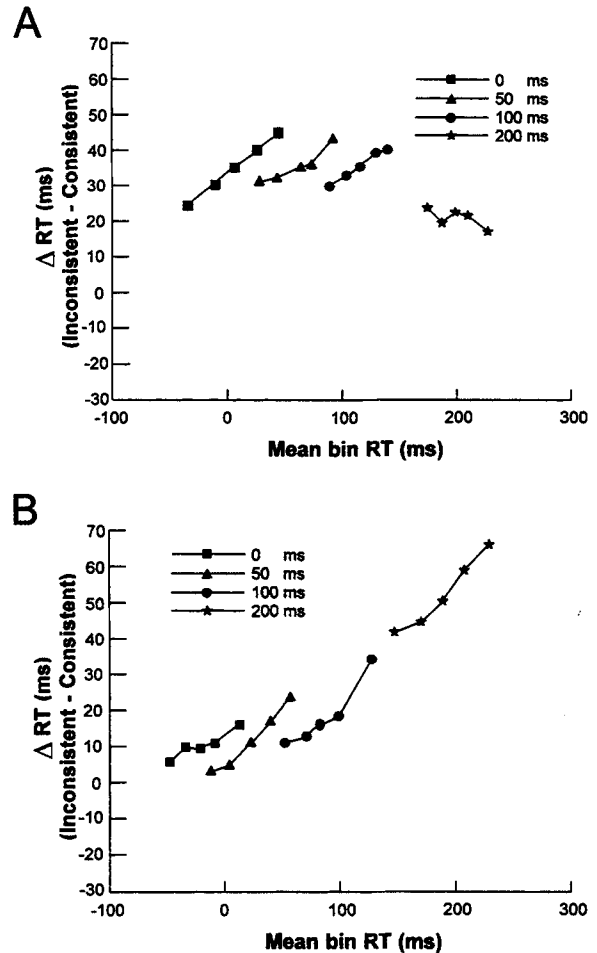


Figure 11. A and B: Distributional plots for simulated data (reaction time [RT] – neutral) in Experiment 1. The abscissa in this and all other distributional plots consists of the difference between the neutral mean RT, and the overall mean RT for the consistent and inconsistent conditions. This sometimes causes the mean bin RT to be negative. (See also Footnote 8.)

In order to simulate the effect of differences in retinal density, we set the initial input to the irrelevant stimulus units for the flankers to .7 for the vertical condition instead of 1.0, as in previous simulations. (The input was 1.0 for the horizontal condition, as well.)

2. *Stimulus and response thresholds (θ_s and θ_r).* Hommel (1997) used the identical set of letters as target stimuli and flankers. This made the task more difficult, because it involved greater discrimination than when target stimuli merely overlap with the set of flankers, without being identical (as was the case in our own two experiments in which the overlap was between colors and color words). We implemented this increase in task complexity by increasing the threshold values. Moreover, because differences in retinal density mean that the irrelevant stimulus produces more interference in the horizontal than in the vertical condition, the stimulus thresholds were set higher in the horizontal than in the vertical condition. Thus, for the

horizontal condition, $\theta_s = .7$ and $\theta_r = .6$, whereas in the vertical condition, $\theta_s = .6$ and $\theta_r = .6$. All other parameters were identical to those used to simulate Experiments 1 and 2.

Simulation 1: Mean reaction times and effect sizes. The empirical as well as the simulated data for both horizontal and vertical conditions of Hommel's (1997) Experiment 2 are shown in Table 5 in a side-by-side comparison. The simulation was run with the parameter values indicated above. Regression yielded a correlation between the empirical and simulated data of .9968 ($R^2 = .9936$) for the horizontal condition and .9999 ($R^2 = .9998$) for the vertical condition. The transformation equations converting time-step units into milliseconds were $ms = (.0292)$ time steps + 386 for the horizontal condition and $ms = (.0289)$ time steps + 373 for the vertical condition.

Simulation 2: Distributional characteristics. As can be seen in Table 5, the simulated means and standard errors matched the empirical data fairly closely. When we made a quintile analysis of the simulated data, the results also matched Hommel's (1997) analysis closely for both the vertical and the horizontal conditions (see Figure 12).

De Jong et al.'s (1994) Experiment 3

The task in De Jong et al.'s (1994) Experiment 3 consisted of left-right keypress responses made to the target words *high* or *low*, presented either to the left or the right of a central fixation point, above or below a set of Xs (a DO Type 7 task). De Jong et al. (1994) used distributional analyses to examine the time course of the S-S and S-R consistency effects.

Interestingly, the mean RTs for each of De Jong et al.'s (1994) four experimental conditions (S-S consistency \times S-R consistency) can be expressed as a linear transformation of the mean RTs obtained by Hommel (1997) in his *horizontal* condition ($r = .9944$). We, therefore, used the identical simulation for matching the mean RT data in De Jong et al.'s (1994) Experiment 3 as we had used to simulate the data of the vertical condition in Hommel's (1997) Experiment 2, and we rescaled the data. In particular, in order to convert time step units into milliseconds we used the following equation instead of the conversion equation we had used for Hommel's (1997) data: $ms = (.0175)$ time steps + 439. This

produced a correlation of .9996 between De Jong et al.'s (1994) empirical data and our simulation.

Even though there was a high correlation between the mean RTs of De Jong et al.'s (1994) and Hommel's (1997) experiments, as well as between the empirical and the simulated means of De Jong et al.'s (1994) experiment, important differences emerged from a comparison between the distributional plots of De Jong et al.'s (1994) empirical data (Figure 13A) and our simulated data (Figure 13B). These differences imply the presence of differences in the time course of the underlying processes between the empirical and the simulated data. In particular, the simulated data, rescaled from the simulation of Hommel (1997), show an almost flat time course for the S-S inconsistent condition (see Figure 13B), whereas De Jong et al.'s (1994) data (see Figure 13A) decreased gradually from a roughly 15-ms effect to an almost -20-ms effect. In the SS consistent condition, the simulated data decreased drastically from a 15-ms effect to approximately a -10-ms effect and ranged (on the abscissa) between only approximately 450 ms and 550 ms. In contrast, De Jong et al.'s (1994) empirical data decreased from a roughly 20-ms effect to just more than a 0-ms effect and ranged between 450 and 750 ms.

Thus, although the mean RTs of Hommel's (1997) and De Jong et al.'s (1994) experiments were very similar (i.e., were linear transformations of one another), their RT distributions displayed extremely different characteristics, as indicated by the fact that the same simulation that accurately captured *both* the means and the distributions of Hommel's (1997) data was able to capture the means *but not the distribution* of De Jong et al.'s (1994) data.

This raises the question of whether the parameter values used in the simulation can be modified in a principled manner (e.g., based on the differences between Hommel's, 1997, and De Jong et al.'s, 1994, experimental conditions) to yield the difference in the distributional characteristics of these two sets of data while maintaining the close fit that we have obtained for their means. To accomplish this we changed the stimulus and response threshold (θ_s and θ_r) parameters. In the previous section we argued that in order to simulate Hommel's (1997) data, it seemed reasonable to increase the threshold values because the set of irrelevant

Table 5
Empirical and Simulated Values for Hommel's (1997) Experiment 2

S-S	S-R empirical data					S-R simulated data				
	Consistent		Inconsistent		Δ	Consistent		Inconsistent		Δ
	RT	SD	RT	SD		RT	SD	RT	SD	
Horizontal condition										
Consistent	528	2.3	536	4.3	8	523	2.6	539	2.0	16
Inconsistent	637	9.6	635	9.8	-2	641	6.8	631	5.2	-10
Vertical condition										
Consistent	495	3.2	522	2.6	27	495	2.0	522	1.7	27
Inconsistent	543	4.5	540	5.2	-3	543	4.8	539	3.5	-4

Note. S-S = stimulus-stimulus; S-R = stimulus-response; RT = reaction time.

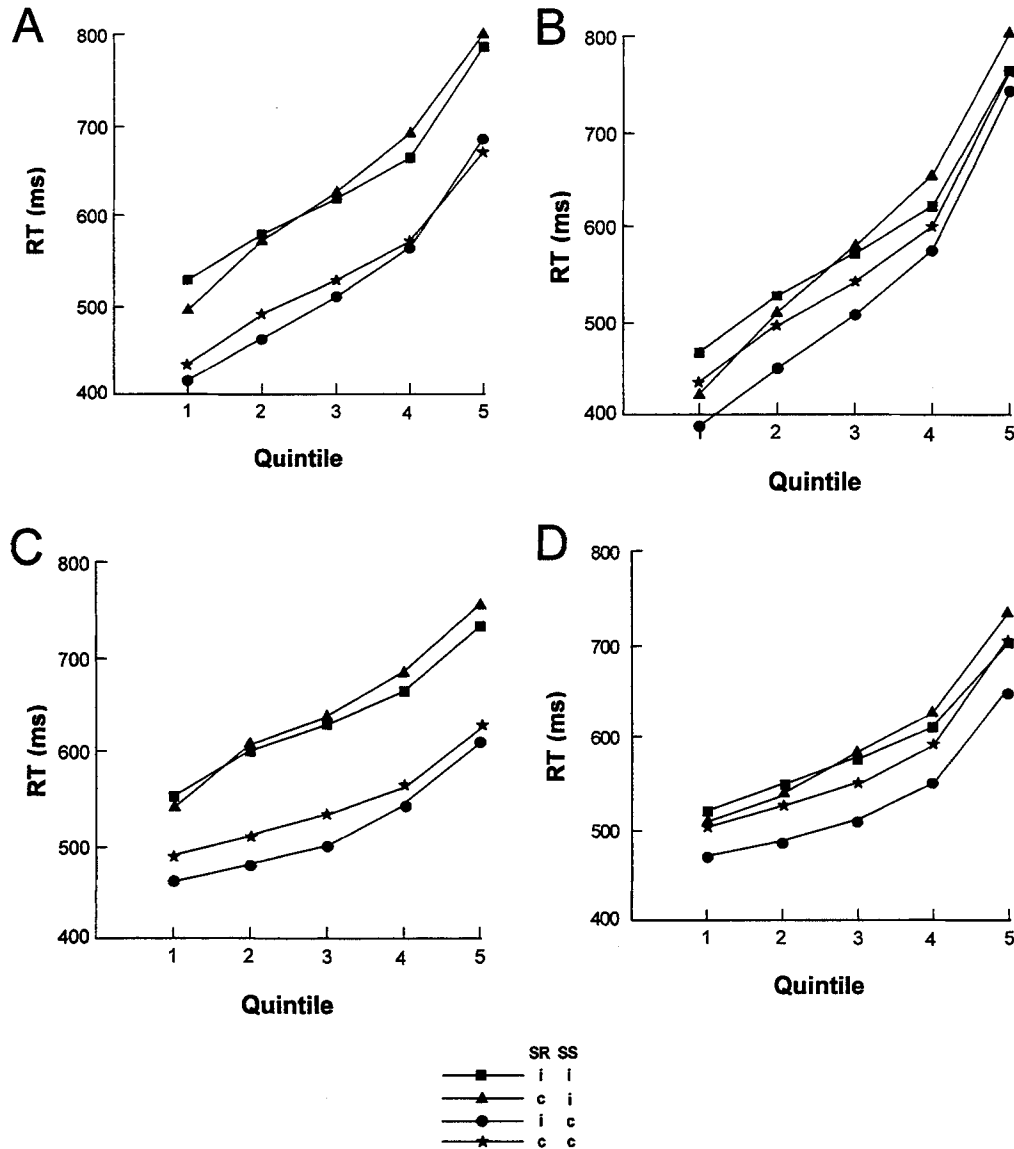


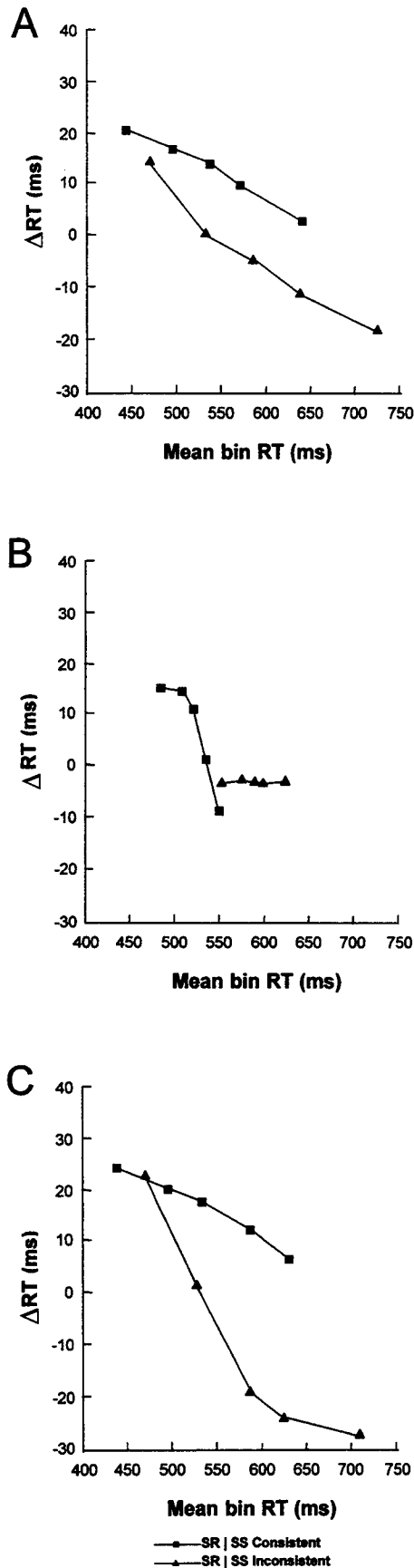
Figure 12. A and B: Empirical data from Hommel's (1997) Experiment 2. C and D: Simulations of Hommel's (1997) data for Experiment 2. SR = stimulus-response; SS = stimulus-stimulus; i = inconsistent; c = consistent.

stimuli (flankers) was identical to the set of relevant stimuli (the same set of letters in both cases), thus making stimulus discriminability difficult. In De Jong et al.'s (1994) experiment, however, the relevant and irrelevant stimuli were physically different (spatial position and position words); in this sense De Jong et al.'s (1994) experiment was similar to the two that we reported in this article, in which the relevant and irrelevant stimuli consisted of colors and color words. Consequently, for the new simulation of De Jong et al.'s (1994) data, we set the stimulus and response thresholds equal to .1 less than the values used in the simulation of Hommel's (1997) horizontal condition (so $\theta_s = .6$, $\theta_r = .5$).

Aside from this change, all the other parameters values used in the simulation of De Jong et al.'s (1994) data were

identical to the parameters used to simulate Hommel's (1997; horizontal condition) data, above. The simulation was run with noise and 300 observations per condition.

When the simulation was run with these new parameter values, the correlation between the means of the simulated data and De Jong et al.'s (1994) empirical data dropped slightly (from $r = .9996$ to $r = .9565$) but was still high. The equation used to convert time steps to milliseconds was $ms = (.0597) \text{ time steps} + 265$. However, not only did the correlation between the simulated and empirical means remain high, but the distributional analyses of the new simulated data (see Figure 13C) also provided a much better fit to the distributional plot of De Jong et al.'s (1994) empirical data (Figure 13A) than the earlier simulation did.



Comparisons With Other Related PDP Models

Locus of Inhibition in the Network

Unlike other PDP models that include within-module inhibition in their architecture (e.g., Cohen & Huston, 1994; Zorzi & Umiltà, 1995), we chose not to have such connections but instead to have inhibition between noncorresponding units of different modules. Even though within-module inhibition is consistent with the graded, random, and interactive network (GRAIN) model (McClelland, 1993)—which in many ways is the normative PDP model—reciprocal, within-module inhibition can lead to an explosive feedback loop that often causes such models to generate unreasonable data. Different models have addressed this problem in different ways. For example, Zorzi and Umiltà (1995) constrained their model so that “only positive activations propagate through connections” (p. 194). Cohen and Huston (1994) resorted to a similar device and constrained activation values between zero and one. These constraints seem rather arbitrary ways for eliminating the feedback effects of within-module feedback and make simulation of the effects of below-zero inhibition impossible (a matter that we discuss in a follow-up article; Kornblum, 1999). In the absence of any compelling evidence in support of within-module inhibition, therefore, we elected to have between- rather than within-module inhibition in our model.

Noise

Gaussian noise is usually added during the simulation process to impart the stochastic characteristics of empirical data to the simulated data. However, there are both theoretical and empirical reasons to use skewed (non-Gaussian) distributions when adding variability to RT parameters. Empirically, RT distributions are ordinarily skewed and appear to resemble a gamma distribution (see Luce, 1986). Many parameters have theoretical lower limits that Gaussian noise would exceed in absurd ways. For example, adding Gaussian noise to the threshold parameters would lead to the stimulus or response threshold sometimes being less than zero, which is conceptually untenable in the framework of the model. As a result, we chose to use noise taken from a gamma distribution, which is a positive-skewed distribution that is always greater than zero. The shape parameter of the distribution was chosen so that the distribution would have a lower bound at zero for all parameters, the mean would be the expected value of the parameter (i.e., the value that the parameter would have without noise), and the variance would be equal to the “noise” parameter ϵ .

Figure 13 (opposite). A: Empirical data from De Jong et al.'s (1994) Experiment 3. B: Simulation of De Jong et al.'s (1994) data for Experiment 3, using the same parameters as those used for the simulation of Hommel's (1997) data (Figure 12C and 12D). C: Simulation of De Jong et al.'s (1994) data for Experiment 3, using parameters different from those used in B. RT = reaction time; SR = stimulus–response; SS = stimulus–stimulus.

We also assumed that noise is present from the input modules onward, throughout all the processing stages in the network, including noise at the start of the execution phase. Therefore, we introduced noise in the input function of each unit in the model,

$$\text{net}_j(t) = \sum o_i(t)w_{ij} + \epsilon, \quad (10)$$

where ϵ is a gamma random variable. This placement of the noise (if not the distribution) is consistent with Cohen et al. (1990); however, it is in sharp contrast to Zorzi and Umiltà (1995) who (a) added noise to the activation rather than to the input functions and (b) did so for units in the response layer only. Thus,

$$a_j(t) = \alpha \text{net}_j(t) + (1 - \alpha)a_j(t - 1) + \epsilon, \quad (11)$$

which results in the RT variance always being directly proportional to RT. However, we know that this relation is often reversed. For example, S-R inconsistent conditions may have either larger or smaller variances than their corresponding S-R consistent condition with faster RTs (e.g., De Jong et al., 1994, Zhang & Kornblum, 1997, and the data in the present study). Zorzi and Umiltà's treatment of noise, therefore, leads to incorrect data. Our model, however, deals with these relationships well (see the simulation of Experiment 1).⁹

Input Representation and Attention

Most recent PDP models of spatial attention (e.g., Cohen et al., 1990; LaBerge & Brown, 1989; Mozer, 1991; Phaf et al., 1990; Servan-Schreiber, 1990) have based their representation of attention on the idea that attention serves to prime feature detectors for attended locations. Our model breaks with this tradition by suggesting that *attentional priming* has a time course. Specifically, according to our model, unattended (irrelevant) stimuli initially provide just as much input as attended stimuli. However, this input is subsequently suppressed. The distinction that we make between irrelevant stimulus *input* and irrelevant stimulus *activation* (see Figure 6) is what makes it possible for the activation of the irrelevant stimulus to follow a rising and falling pattern, which is one of the critical features of our model.

Thus, in Zhang's (1994/1995) model, input to the irrelevant stimulus dimension was weighted by a constant scaling factor ($0 < \text{input} < 1$) that made it consistently weaker than the input to the relevant stimulus dimension (input = 1). In our model, input to both modules is initially the same (input = 1), and only after some period of time (τ) does this input begin to decrease (linearly at some slope [ρ]). This decrease can be interpreted as either active attentional suppression of stimulus input or a fall-off of stimulus input due to inattention. Either way, these inputs result in the differential activation curves for the relevant and irrelevant module units shown in Figure 6.

The Seriality Assumption

Since the publication by McClelland (1979) of his cascade model, most connectionist models of RT have assumed the underlying processing to be continuous (e.g., Cohen et al., 1990; Zhang, 1994/1995; Zorzi & Umiltà, 1995). The lure of this assumption rests in large part on the demonstration that models that incorporate it can account not only for mean RT effects that stage models had previously accounted for, but also for other effects that were problematic for stage models, such as under- and overadditivity (see McClelland, 1979, for details).

We have made numerous (unsuccessful) attempts to fit the time-course data from Experiment 2 by means of a traditional, continuous, three-layer connectionist network; these attempts did not have a stimulus-layer threshold, nor were the response units clamped to zero. We have also tried other architectures, including two-layer networks that did include a stimulus threshold (and thus were identical to the architecture that we finally decided to adopt) but did not have the response units clamped to zero—again with no success. As long as we retained the assumption that both S-S and S-R effects are caused by a single underlying irrelevant stimulus activation function, none of the various architectures that we tried (and we do not claim to have tried all permutations and combinations) was successful in accounting for the time-course data of our experiments.

The reason for these failures is quite straightforward. When viewed in terms of our model, what characterizes the results of Experiment 2 (replicated in Experiment 1) is the finding that when SOA experimentally shifts the irrelevant stimulus activation curve in time, the effective segments of that curve have been differentially altered in the stimulus and in the response stages (see Figure 7). That is, given that both S-S and S-R consistency effects are a function of the activation level of the irrelevant stimulus, and that the S-S effect is influenced by an earlier part of that activation curve, whereas the S-R effect is influenced by a later part, it necessarily follows that these two consistency effects have different time courses. Given the characteristics of the time-course data presented here, a continuous model would have to make some kind of ad hoc assumption to account for the differences observed between S-S and S-R consistency effects. For example, such a model might account for these data by claiming that S-S and S-R consistency effects arise from two separate activation curves that were nonetheless identical except for their timing. Alternatively, a continuous model could assume that the activation curve responsible for these effects somehow influenced the relevant stimulus and response units differently, thus giving rise to different effects. Although a continuous model could make such claims and thus retain the notion of processing continuity, such assumptions would all be ad hoc and would diminish the parsimony of the model.

The model we present here, however, begins with three

⁹ In fact, the variance of RT may depend on where one is on the irrelevant activation function when S-S or S-R processing is taking place.

basic simplifying assumptions about the processing of S-S DO and S-R DO:

1. S-S and S-R effects are due to activation of the same underlying irrelevant stimulus activation curve.

2. This irrelevant activation curve influences relevant stimulus and response units in the same way (cf. Equations 4, 5, 8, and 9).

3. The size of the (S-S or S-R) consistency effect is proportional to the amount of (irrelevant stimulus) activation during the period of time that (S-S or S-R) DO is able to influence information processing for the task.

These three assumptions seem to us parsimonious in that S-S and S-R overlap are processed in fundamentally the same way. However, given these three assumptions, the only way that S-S and S-R consistency effects can end up having different time courses is if the time epochs during which these differential time-course properties are generated (the stimulus and response stages in our model) are themselves separate and distinct. Put another way, given these assumptions, a completely continuous model (in which the influence of S-S DO and S-R DO are completely temporally overlapping) cannot account for differential time courses for the S-S and S-R effects. This is because a model that requires the influence of DO on information processing to occur in a single (i.e., the very same) time epoch would have to predict identical time courses for S-S and S-R consistency effects. In the absence of any strong argument against any of our three simplifying assumptions, therefore, it seems appropriate to retain them and thus adopt a stagelike, instead of a continuous, model.

The Neurophysiological Evidence

There is a class of arguments that has often been made against stage seriality and that appears to provide a compelling reason to abandon some of our assumptions. In particular, much (but certainly not all) of the ERP data in the literature appears to support a continuous rather than a discrete view of information processing. These same data have also been cited as evidence to argue that the effects of irrelevant stimuli are mediated by a response, rather than a stimulus, activation function (e.g., De Jong et al., 1994; Hommel, 1997). These two ERP-based views are related. We begin by examining some of the empirical evidence.

Eriksen, Coles, and their colleagues (Coles, Gratton, Bashore, Eriksen, & Donchin, 1985; Eriksen, Coles, Morris, & O'Hara, 1985; Gratton, Coles, Sirevaag, Eriksen, & Donchin, 1988) have reported a variety of ERP, LRP, and electromyographic (EMG) data that they have interpreted as supporting the continuous processing and the response competition hypotheses as accounts of the consistency effects that they observed in their RT data with flanker tasks (Type 4, S-S DO).¹⁰ Eriksen et al. (1985) and Coles et al. (1985) both reported what has now become a standard finding with flanker tasks: When the flankers are inconsistent with the target (S-S inconsistent), RT is longer than when they are consistent (S-S consistent). They also reported significant EMG signals in the incorrect hand on flanker-inconsistent (S-S) trials. In addition, Coles et al.

(1985) and Gratton et al. (1988) found an initial LRP asymmetry toward the side of the incorrect response on flanker-inconsistent trials. Because EMG signals are generally accepted as pure indices of motor activity, and because the stimuli in the standard flanker tasks are not asymmetrically lateralized, these authors interpreted these results as supporting the continuous processing and the response competition hypotheses (Coles et al., 1985; Eriksen et al., 1985; Gratton et al., 1988; see also Eriksen & Schultz, 1979). However, a closer examination of these data reveals that not only are they perfectly consistent with views that do not postulate either continuous processing or response competition, but the EMG data actually *fail* to support these hypotheses. We first take a closer look at the EMG data reported by Eriksen et al. (1985) and follow with an examination of the LRP data.

Eriksen et al. (1985), using a standard, two-choice flanker task, reported significant EMG activity in the incorrect hand on 40% of the flanker-inconsistent trials. Because this hand would have been the correct response if the flankers had been the targets on those trials, they interpreted these EMG signals as reflecting an automatic response process triggered by the flankers. According to the interpretations of Eriksen et al. (1985), Coles et al. (1985), and Gratton et al. (1988), this is the same automatic response activation process that generates the competition between the correct and the incorrect responses, which eventually leads to the longer RTs in the flanker-inconsistent conditions: "Response competition . . . can be viewed as the reciprocal inhibition of competing response structures . . . in which the subthreshold activation of one response leads to a delay in the execution of the other" (Gratton et al., 1988, p. 331). Note, however, that they also found a significant flanker consistency effect on the remaining 60% of the flanker-inconsistent trials for

¹⁰ Even though we originally classified the Eriksen flanker task as DO Type 4 (and used this classification in the present article), this may turn out to be too simplistic a scheme, for there are at least two variants of the flanker task that need to be considered: (a) the standard version, in which the same stimuli are used as targets and flankers (e.g., the digits 3 and 6 are used both as targets and as flankers on alternate trials); and (b) the less standard task, in which different stimuli are used as targets and flankers (e.g., only the digits 3 and 6 are used as targets, and only the digits 2 and 8 are used as flankers). Case-b tasks are the simpler of the two: If the sets of flankers and targets belong to the same category (such as in our 3, 6/2, 8 example)—that is, they have DO by virtue of category membership—then this is a clean case of Type 4, and all the predictions of the model for that type of ensemble hold. Similarly, if the sets of targets and flankers belong to different categories, (e.g., only the digits 3 and 6 are used as targets, and only the colors blue and green are used as flankers)—that is, they have no DO—then this is a Type 1 ensemble, and again, all the predictions for that type of ensemble should hold. Case-a tasks start out in the same way as Case-b tasks. However, with practice the targets (and *a fortiori* the flankers), even though they do not overlap with the responses, do become associated with them and hence develop a functional equivalent of S-R DO (see, e.g., MacLeod & Dunbar, 1988). This means that the standard flanker task (Case a) starts out as a Type 4 or a Type 1 and gradually, with increasing practice, acquires Type 3 properties as well.

which there was *no* EMG activity in the incorrect hand. (Eriksen et al., 1985, noted that response competition may not be the only process at work: "... competition occurs at preparatory levels ... [It] may exist at the recognition level ... [There is] the possibility that there are also interference effects at the input level ..." [p. 167].) Furthermore, the size of the flanker consistency effect (in RT) is approximately the same for trials with and without incorrect EMG signals,¹¹ which clearly violates the hypothesis that EMG is a measure of the response-activation-and-competition-based mechanism underlying the flanker consistency effects in RT. The overall RT for trials with incorrect-hand EMG signals was, of course, much slower than for trials without.

These data can easily be accounted for by models that assume neither continuous processing nor response competition (e.g., Mordkoff, 1995). For example, it is possible that the process generating the incorrect EMG signals on 40% of the flanker-inconsistent trials (and slowing the RT on those trials) is a separate (though related) process from the one giving rise to the flanker consistency effects in RT (as Mordkoff has noted, Coles et al.'s, 1985, causal inference in this regard is based on correlational evidence). Thus, one tentative, plausible interpretation of these and similar EMG data is that incorrect-hand EMG signals on correct response trials represent erroneous responses that were "caught" and corrected before execution but were late in processing.

Viewed in this way, these data become perfectly consistent with the serial nature and stimulus-stage account of the flanker, or with S-S consistency effects postulated by the DO'97 model. The DO'97 model's account for errors is basically the standard connectionist's account: Variability in processing due to noise occasionally leads to activation of an incorrect unit reaching threshold (see, e.g., McClelland, 1993). In the DO'97 model this can occur at either the stimulus stage, or the response stage, or both. Consider flanker tasks such as those used by Eriksen et al. (1985). According to the model, whether the flankers are consistent with the target or not, their presentation automatically triggers irrelevant stimulus activation. If the flankers are inconsistent with the target (S-S inconsistent), this function slows the rate of accumulation of activation in the relevant stimulus unit. At the same time, because of the automatic connection between the irrelevant stimulus unit and its corresponding (but erroneous) unit in the relevant stimulus module (see Figure 5), activation in that "relevant" (but erroneous) unit increases. Now that activation is increasing in two units in the relevant stimulus module—one correct (and triggered by the relevant stimulus) and the other incorrect (and triggered by the irrelevant but overlapping stimulus)—the relative probability that activation in the erroneous relevant stimulus unit will reach threshold becomes significant, and activation in both units could reach threshold. If this happens (which is possible if they both cross threshold sufficiently close in time), they will each trigger the response to which they are connected by the controlled line. If activation in the response unit that was erroneously triggered by the *irrelevant* stimulus (the flanker) reaches the response threshold first, the result is an error. If activation in the response unit triggered by the correct

relevant stimulus reaches the response threshold first, the other response unit (triggered by the incorrect relevant stimulus) may still have enough accumulated activation left during the response stage to show up as either EMG signals in the wrong hand, on some percentage of the trials, or as LRP asymmetries toward the incorrect response, or both. Thus, such observations do not necessarily imply either continuous processing or response competition; nor do they preclude such effects being generated by S-S inconsistencies in a stimulus-processing stage, as postulated in the DO'97 model.

We now turn briefly to more general issues related to the neurophysiological evidence.

The LRP, which we have already alluded to and which is also sometimes referred to as the "corrected motor asymmetry" (De Jong, Wierda, Mulder, & Mulder, 1988), is one of the principal psychophysiological measures on which cognitive or processing inferences are based. Basically, the LRP is a difference curve from which possible hemispheric biases have been removed (see Coles, 1989, and Gratton et al., 1988) to reveal the net asymmetry between the evoked potentials recorded at the left-right electrodes C3/C4 or C'3/C'4 (see Jasper, 1958). When such curves are derived from tracings at other, usually more posterior, electrodes, they have been called "event-related lateralizations" (ERLs; Wascher & Wauschkuhn, 1996). Two separate components have been identified in the LRP: The later, principal one, reaches its peak together with the overt response and is clearly response related; the other, which occurs earlier and before the overt response, consists of a lateralization that has also been interpreted as response related (e.g., Coles, Gehring, Gratton, & Donchin, 1992). However, this interpretation may be equivocal.

Because ERPs provide a continuous record of brain activity occurring between stimulus onset and response execution, it has been tempting to believe that such direct observations of the postulated, intervening, cognitive mechanisms would shed more light on them than the behavioral evidence on the basis of which such mechanisms were postulated in the first place. This, however, may be illusory, at least in part. It is certainly the case that such observations provide additional data for, as well as additional constraints to, our speculations. Whether they resolve the issues at hand, however, is a different question. For example, Miller (1991) has succinctly noted that "it is extremely difficult to find cases in which psychophysiological evidence conclusively answers ... questions about the discreteness or continuity of information processing ... [E]very argument from ERPs *presupposes knowledge of the information-processing significance of the component under study*" [italics added] (p. 252; see also Meyer, Osman, Irwin, & Yantis, 1988). Thus, much of the ERP evidence that has been adduced in support of a continuous view of information processing is also compatible with a multiple-discrete-type view as described by

¹¹ These comparisons are necessarily tentative, because although 40% of the inconsistent trials had incorrect EMG signals, only 8% of the consistent trials had incorrect EMGs, resulting in vastly unequal sample sizes.

Miller (1982), or with other views, as we have shown previously. In addition, in a number of cases in which one might have expected ERP data to support the continuous view, the evidence appears to support the discrete view instead (Coles, De Jong, Gehring, & Gratton, 1991). For example, Rosler and Finger (1993), using an Eriksen flanker task in a direct test and basing their conclusion on ERP data, reported that the transition between stimulus processing and response execution is discrete, not continuous. Smid, Mulder, and Mulder (1990) reached a similar conclusion from a similar study.

A separate but closely related question is whether the LRP is a pure measure of motor preparation or whether it includes, say, sensory or cognitive components. One reason—certainly not the only reason but one that has a great deal of face validity—that the LRP has traditionally been viewed as a measure of response readiness (e.g., Coles, 1989; Gratton et al., 1988) is that the C3/C4 (C'3/C'4) electrodes, used to record the data for the LRP calculation, are located over the primary motor areas of the brain. However, we know that “motor” and “sensory” neurons are not segregated in an all-or-none fashion in different areas of the brain. Instead, they are distributed as networks with varying proportions of sensory and motor cells in many parts of the brain (Requin, Riehle, & Seal, 1993). This finding alone brings into question the macromodular structure-function assumption that underlies the location-based, functional interpretation of ERPs. Even if this assumption were valid, however, it has been shown that, depending on the orientation of the generating dipole (e.g., Brunia & Van den Bosch, 1984) and because of volume conduction, identifying the exact locus of the generating source of an EEG signal is often extremely difficult and requires special procedures (e.g., surface Laplacian; see Nunez, 1990). We know of no published study addressing the interpretation of the LRP that used these special procedures to verify the source of the signals.¹²

Furthermore, lateral asymmetries have been recorded from sites other than C3/C4. For example, early asymmetries have been reported from occipital and parietal electrode sites (e.g., Luck, Hillyard, Mouloua, Woldorff, Clark, & Hawkins, 1994). Wascher and Wauschkuhn (1996) made the interesting observation that investigators using central electrode sites have been those primarily interested in response processes (e.g., De Jong et al., 1988; Gratton et al., 1988; Osman et al., 1992), whereas those using posterior electrode sites have been those primarily interested in attentional processes (e.g., Mangun & Hillyard, 1988, 1991). In their study, Wascher and Wauschkuhn reported ERP asymmetries obtained from both central as well as posterior sites. Their results are illuminating. Using stimuli consisting of a letter plus a filler, presented symmetrically around a central fixation point, Wascher and Wauschkuhn had subjects perform a variety of tasks that all used the same stimuli but differed in their response requirements. Event-related potentials were recorded from eight pairs of symmetrical electrodes going from C'3/C'4 centrally (or frontally) to O1/O2 posteriorly, in addition to Fz, Cz, and Pz (see Jasper, 1958). Recall that the LRP consists of an early and a late component. They found that the peak amplitude of the first—early—

lateralization was greater posteriorly than centrally, whereas the peak amplitude of the second—late—lateralization was greater centrally than posteriorly. Furthermore, the latency of the first component was the same for all tasks and all electrode sites, whereas the latency of the second component differed for S-R consistent and inconsistent conditions at central sites. Wascher and Wauschkuhn concluded that although the second lateralizations, with their peak over the central electrodes, are probably response related, the temporal characteristics and topography of the first asymmetry point to a nonmotoric interpretation of the early LRP. Mordkoff (1995) has also shown that the flanker effects that Coles et al. (1985) reported and attributed to response conflicts could, in principle, have been generated by premotor processes.

All these reinterpretations and suggestions of alternative explanations are, of course, tentative and require a great deal more work both empirically and theoretically. However, it is clear that many of the ERP, LRP, and EMG findings that might have been viewed as disconfirming the DO'97 model are, in fact, consistent with its two-stage, serial structure. The evidence, therefore, needs to be viewed with caution and may even be reinterpreted so as to be reconciled with the model.

General Discussion

The Experiments

Two experiments were conducted that examined the time course of the effects of irrelevant stimuli by presenting the irrelevant stimuli before the relevant ones at varying time delays. The irrelevant stimulus overlapped with either the relevant stimulus (S-S overlap Type 4), the response (S-R overlap Type 3), or both (Type 7). The results are clear: Rarely, if ever, were the effects of S-S and S-R overlap the same at any one delay. Examination of these effects over delays (e.g., Figure 3B) reveals that the effects of S-S overlap slowly rose and then fell, whereas the effects of S-R overlap displayed an extremely rapid rise, followed by a fall. The effects of S-S and S-R overlap thus appear to follow very different time courses.

This observation, which can be made purely on the basis of the mean RTs (see Figure 3A and 3B and Tables 1 and 2), is supported in finer grained detail by the distributional analyses (see Figures 2 and 4). In particular, the mere suggestion of an increase, based on the mean RTs, in the effect of S-R overlap at short delays is substantiated by the distributional plots of the S-R overlap data at 0- and 50-ms delays for Experiment 1 and at 0-ms delay for Experiment 2. Similarly, the small and practically nonexistent effects of S-S overlap, as indicated by the means, is substantiated by the flat distributional plots of the S-S overlap data at delays of 0 and 50 ms for Experiment 1. Finally, the nonmonotone

¹² However, a small group of investigators at the CRNC-CNRS in Marseille, including M. Bonnet, T. Hasbroucq, and F. Vidal, is currently working on this problem and has several articles in preparation.

aspect of these effects over delays, as displayed by the means, is confirmed by the distributional plots of the S-S and S-R consistency effects at delays that, in principle, straddle the point in time when the irrelevant activation function is at a maximum (see Figures 2A and 4A, 4C, and 4D).¹³

The Model

These data were fit by a computational model whose PDP architecture and functional principles implemented the basic principles of the DO model (Kornblum, 1992, 1994; Kornblum et al., 1990), with one important modification. In particular, the model includes two layers of modules that correspond to a stimulus-processing and a response-production stage. The modules in each layer (stages) are composed of units and have activation thresholds that determine the point in time when activation is initiated in the next stage. For example, no processing takes place in the response-production stage until activation in the stimulus stage has reached threshold. This particular property implements the seriality assumption between stages present in earlier versions of the DO model. However, unlike these earlier versions, the present computational version of the model does not assume independence between these stages.

Stage Independence and Temporal Order

In particular, we assumed that all the features of an external stimulus generate an input to the appropriate stimulus units and that the values of all these inputs are initially identical and maximal. After a brief period of time, during which the relevant features of the stimulus are distinguished from the irrelevant ones, the inputs associated with the irrelevant features decay, whereas the inputs associated with the relevant features remain constant. As these various inputs are being fed into the appropriate stimulus units, they generate activation functions whose values approximate the input levels. Thus, because the inputs produced by the relevant stimulus remain constant, the activation functions associated with these features are ogival in shape and gradually approach a constant, maximum value. Similarly, because the inputs being produced by the irrelevant stimulus features start decaying shortly after being triggered, the activation functions associated with the irrelevant features have a roughly inverted U shape.

The activation of the irrelevant features becomes critical when there is some relationship (DO) between the irrelevant features and some aspect of the task—either stimulus or response. If there is no relationship (no DO), then the irrelevant stimulus activation has no effect. If the irrelevant feature is related to the stimulus (S-S overlap), then it affects the rate at which the activation function of the relevant stimulus unit reaches threshold: speeding it up if it is consistent and slowing it down if it is inconsistent. If it is related to the response (S-R overlap), then it will have the same effect in the response unit: increasing the rate at which the response activation reaches threshold when it is consistent and decreasing this rate when it is inconsistent. If it is

related to both, then of course it will have the appropriate effects in the appropriate units of each layer (stage).

What is critically important to note, however, is that the magnitude of the influence of the irrelevant stimulus on the activation levels of either the stimulus or the response stage is directly determined by the level of activation of the irrelevant stimulus at the onset of either the stimulus-processing stage or the response-selection stage, respectively. (Recall that the level of irrelevant stimulus activation changes through time and describes an inverted U-shape function.) As we have seen, starting the irrelevant stimulus activation process early by using SOAs can modify the value that the irrelevant stimulus activation function has at the onset of the stimulus-processing stage. Because S-S overlap changes the duration of the stimulus-processing stage, S-S overlap results in a change in the value of the irrelevant stimulus activation curve at the onset of the response-selection stage. In this way, the duration of the response-selection stage depends on the duration of the stimulus-processing stage. This dependency arises, in effect, because the two stages are serially ordered: Changes in the duration of the first stage influence the time at which the second stage is allowed to begin, whereas the duration of the second stage depends on when it begins. Empirically, this is observed as an S-S \times S-R interaction.

Temporal Overlap

Although this new version of the DO model includes temporally overlapping processes, the principles of temporal overlap that we assume in our model differ in several fundamental respects from those proposed by Hommel (1993). First, we have retained the notion, present in the original DO model, that the stimulus and response stages underlying these S-R compatibility tasks are serial. Hommel (1993) assumed that the stimulus and response stages operate asynchronously, so that information is continually being passed from the stimulus to the response stage.

Second, in our model, all the irrelevant stimuli generate an activation curve, regardless of what they overlap with. It is only when it comes to specifying the consequences of these irrelevant stimuli that the particular nature of their overlap becomes important; even then, their actions are identical irrespective of whether they overlap with the stimulus or the response. It is in the site of their actions that they differ. For Hommel (1993), however, the irrelevant stimulus, whose decay and subsequent temporal overlap with other processes generate the various effects predicted by his temporal overlap model, must have DO with the response. If the irrelevant stimulus overlaps with the relevant stimulus, it behaves very differently. Hommel (1993) dealt with these differences between S-S and S-R overlap by assuming that the stimulus and response stages process

¹³ One of the puzzles posed by our interpretation of the distributional plots is that there are times when these plots fail to follow the slope of the time-course function suggested by the mean RT data. This may be a problem of noise or sampling size; in any event it is a problem that needs further work.

information asynchronously, rather than serially, as we assume in our model.

Third, like De Jong et al. (1994), Hommel (1993) assumed that the S-R consistency effects necessarily decay with time; our model permits a brief, and sometimes long, period of time in which the S-R consistency effects may rise, as they have been observed to do (this period is considerably longer in the case of S-S overlap). Thus, even though we have had to modify the independence assumption of the earlier versions of the DO model, we suggest that to the extent that the present computational version of the model is able to simulate, and to account for, in a principled manner, not only the interactions between S-S and S-R consistency but their shape as well, Hommel's (1993) assertion that such effects are inconsistent with our seriality assumption is incorrect.

Finally, the fact that the distributional plots of our simulated data match the distributional plots of four sets of empirical results reasonably well is strongly suggestive that our model may have captured an important aspect of performance in such tasks.

This article has dealt with DO Types 3, 4, and 7. In a forthcoming article (Kornblum, 1999) we will deal with DO Types 2, 3, 5, and 8, using basically the same computational model, in an attempt to show that all these compatibility tasks share a common cognitive processing structure.

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Appendix

The DO Taxonomy

The DO taxonomy consists of eight S-R ensembles (column 1 in the table below), or tasks (column 6), arrived at by combinations of the DO between the response, the relevant stimulus, or the irrelevant stimulus (see columns 2, 3, and 4). In the literature, several of these tasks are commonly referred to by—what has become—an ambiguous terminology. We propose, and have adopted for ourselves (see Kornblum & Lee, 1995, Appendix), the convention of using the term *congruence effects* (also *map-*

ping effects) for the effects or correspondence and noncorrespondence when the *relevant* stimulus and the response dimensions overlap. When the *irrelevant* stimulus dimension overlaps with either the response or the relevant stimulus dimension, we call these *consistency effects*. This permits each task corresponding to an ensemble type to be labeled according to the descriptive, generic, dimensional properties of that task (see column 6).

Ensemble type	DO			Common examples	Generic task type
	S-R relevant	S-R irrelevant	S-S irrelevant		
1	0	0	0	RT tasks	Neutral
2	1	0	0	"S-R compatibility" task	Congruence
3	0	1	0	Simon task	S-R consistency
4	0	0	1	"Stroop-like" and flanker tasks	S-S consistency
5	1	1	0	Hedge & Marsh (1975) task	S-R congruence & S-R consistency
6	1	0	1		S-R congruence & S-S consistency
7	0	1	1		S-S & S-R consistency
8	1	1	1	Stroop task	S-R congruence & S-S/S-R consistency

Note. In columns 2, 3, and 4 the numbers 1 and 0 refer to whether there is dimensional overlap (DO) between the aspects of the task indicated in the column headings (as, for example, between the relevant stimulus and the response in column 2): 1 = there is DO; 2 = there is no DO. Even though DO is treated as a binary variable in the taxonomy, it is treated as a continuous variable in the model. S-R = stimulus–response; S-S = stimulus–stimulus; RT = reaction time.

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