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Executive Control of Visual Attention in Dual-Task Situations

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A theory of executive control is presented that proposes that executive processes control subordinate processes by manipulating their parameters, reconfiguring them to respond in accord with the current task set. It adopts C. Bundesen's (1990) theory of visual attention (TVA) and R. M. Nosofsky and T. J. Palmeri's (1997) exemplar-based random walk (EBRW) as the theory of subordinate processes. It assumes that a task set is a set of TVA and EBRW parameters sufficient to perform a task and that set switching involves changing those parameters. The theory solves 2 computational problems that emerge in dual-task situations: the binding problem and the serial order problem. It can perform dual tasks in series or in parallel but prefers the serial strategy because it is faster and it solves the binding problem naturally. The theory accounts for concurrence cost, set-switching cost, crosstalk between tasks, and the modulation of crosstalk by task set.

We live in a world of blooming, buzzing confusion. Many courses of action are open to us every second,.and we often try to follow several at one time. Our struggles in coping with multiple task demands are part of the fabric of modern life, the stuff that novels are made of. Our struggles in multiple-task environments have been interesting to psychologists for a century (e.g., Solomons & Stein, 1896; Welch, 1898), who understood them as phenomena of attention (e.g., James, 1890). Researchers developed experimental paradigms that abstracted and isolated different aspects of the bloom and the buzz, and the literature proliferated (Lovie, 1983). The first systematic theories of attention were developed in the 1950s and 1960s (e.g., Broadbent, 1958, 1971; Kahneman, 1973; Neisser, 1967). They were integrative, trying to model the whole set of attentional phenomena in a single theory based on a few simple principles, such as central bottlenecks (Broadbent, 1958) or limited processing capacity (Kahneman, 1973; Posner & Boies, 1971). The mechanism that accounted for selection between tasks was also responsible for selection within tasks.

The theoretical focus has shifted in the last 20 years, from general to specific, from integrative to analytic. Researchers adopted a divide-and-conquer strategy, addressing the details of individual phenomena rather than the commonalities among them. Some researchers have studied selective attention within tasks, asking how people choose among multiple objects of perception or regions of space (e.g., Bundesen, 1990; Duncan, 1984; Logan, 1996; Treisman & Gelade, 1980; Wolfe, 1994). Others have studied selection between tasks, asking how people perform several tasks at once (e.g., Jolicoeur, 1998; Pashler, 1984; Pashler & Johnston, 1989). These were considered to be different phenomena of attention, explained by different theoretical mechanisms (Johnston, McCann, & Remington, 1995; Pashler, 1991). This research has revealed many important details about individual phenomena and has created several specific theories to account for them.

The success of the divide-and-conquer strategy depends on an implicit assumption that the parts can be fit together to form a coherent whole, like the pieces of a jigsaw puzzle. The ultimate goal of attention research is a single integrative theory that accounts for most of the bloom and the buzz so, eventually, the specific theories must generalize beyond the phenomena they were developed to account for. A theory of one phenomenon should extend to another phenomenon, or it should interface naturally with a theory of the other phenomenon to form a new theory that accounts for both.

One purpose of the present article is to test the assumption that the parts can be fit together by extending one of the most powerful current theories of selection within tasks, Bundesen's (1990) *theory of visual attention* (TVA), to deal with selection between tasks in dual-task situations. TVA was developed to account for a wide variety of single-task situations that require selection within tasks, including whole and partial report (Bundesen, 1987, 1990), feature and conjunction search (Bundesen, 1990; Logan, 1996), item identification (Bundesen, 1990), and flanker tasks (Logan, 1996). Current single-task versions of TVA already have most of the machinery required to run TVA in dual-task situations. We extend TVA to dual-task

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situations by running it twice, once for each task. In order to make it run twice, we had to specify two new (executive) processes that control TVA's response to multiple stimuli.

The success of the divide-and-conquer strategy depends on a second implicit assumption that the whole is no more than the sum of the parts. The individual theories can be fit together to form a complete account of attentional phenomena with nothing important left unexplained. A significant challenge to this assumption has appeared in the recent interest in *executive processing* (Logan, 1985; Meyer & Kieras, 1997a, 1997b; Norman & Shallice, 1986). The requirement to do two things at once (Duncan, 1979) or to switch from one thing to another (Allport, Styles, & Hsieh, 1994; Rogers & Monsell, 1995) creates an emergent need to organize and schedule the elementary, subordinate processes that are recruited to deal with individual tasks. The whole is more than the sum of the subordinates. It includes the executive as well.

The second purpose of this article is to test the assumption that the whole is more than the sum of the parts by proposing a theory of the executive process that controls TVA. We call our theory *executive control of TVA* (ECTVA). It consists of a subordinate process—TVA—that can be programmed to carry out different tasks, and an executive process that programs the subordinate. Our theory of executive processes is grounded in a theory of subordinate processes—TVA—just as theories of subordinate processes are grounded in theories of stimulus and response properties (also see Meyer & Kieras, 1997a, 1997b). Any process, executive or subordinate, can be defined in terms of the inputs it takes and the outputs it gives. The inputs to visual perceptual processes are described in terms of optics: luminances, wavelengths, and so on. The inputs to visual word recognition processes are described in terms of visual features, the frequency with which features and feature combinations appear in print, and so on. A theory of the executive must be grounded similarly in a theory of the states of a subordinate process. The idea that an executive programs a subordinate is rather empty without a theory of the subordinate that says how it can be programmed. Our theory of the executive is grounded in the states of TVA. The input to our executive is a state of TVA, and the output is a change in the state of TVA.

TVA exerts strong constraints over our theorizing about executive processes, because there are only a few ways to change its states and control it. TVA has six different kinds of parameters, three of which are entirely under executive control and one of which is partially under executive control. ECTVA controls TVA by manipulating these parameters. In ECTVA, a task set is a set of TVA parameters that is sufficient to configure TVA to perform a task. ECTVA adds two more kinds of parameters: one representing the time required for the executive process to manipulate TVA's parameters and one representing the manner in which the executive process resets the evidence-accumulation process to enable a response to a second stimulus. The whole is more than the sum of the parts but not much more.

Our investigation focuses on a dual-task situation called the *psychological refractory period* (PRP) procedure, in which subjects make discrete responses to punctate stimuli that appear at precisely controlled intervals (Welford, 1952). We chose this procedure because it is perhaps the most popular of the current dual-task procedures (see Pashler, 1994a) and because it is the focus of an important theoretical controversy over the division of labor between executive and subordinate processes (Pashler, 1989; Pashler & Johnston, 1989; Van Selst & Jolicoeur, 1997, vs. Meyer & Kieras, 1997a, 1997b). Our investigation focuses on three effects that have been interpreted in terms of executive processing in the dual-task literature: crosstalk, set-switching cost, and concurrence cost. We report three experiments that look for these effects in the PRP procedure, and we account for our findings in terms of our theory. The experiments show that crosstalk is modulated by task set—it occurs only when the set is the same for the two tasks—and our theory accounts for that modulation.

The PRP Procedure

A Brief History

Multiple-task situations can be implemented in many different ways. Solomons and Stein (1896), for example, had subjects take dictation while reading prose. Welch (1898) had subjects squeeze a dynamometer while performing mental arithmetic and other tasks and measured the relaxation in subjects' grip when the mental task got difficult. These tasks had a certain ecological validity but did not afford much experimental control. The timing of stimulus events was often under the subject's control rather than the experimenter's. The tasks were continuous and so could be controlled by discrete executive actions that occurred at unknown times (e.g., Broadbent, 1982).

The PRP procedure arose from a need to have precise control over the experimental procedure and over the subject's performance. The PRP procedure achieves these goals by presenting just two stimuli, S1 and S2, with some controlled interval between their onsets, called *stimulus onset asynchrony* (SOA), which ranges from 0 to 1,000 ms in most experiments. Subjects respond separately to each stimulus, performing Task 1 on S1 to produce response R1 with latency RT1, and Task 2 on S2 to produce R2 with latency RT2. The stimuli are typically presented well above threshold, so reaction time (RT) is the main dependent variable. The tasks are well specified, and subjects are instructed to respond as quickly as possible without making errors, so their performance is strongly constrained. A schematic version of a typical PRP experiment is depicted in Figure 1A.

The most basic PRP results are the effects of SOA on RT1 and RT2, depicted in Figure 1B (for reviews, see Bertelson, 1966; Kahneman, 1973; Pashler, 1994a; Smith, 1967; Welford, 1952). Generally, RT1 remains constant over SOA, whereas RT2 is strongly affected. It is largest when SOA = 0, and it decreases substantially as SOA increases from 0. Researchers generally interpret the constancy of RT1 over SOA as evidence that Task 1 was "protected" and the slowing of RT2 at short SOAs as evidence of dual-task interference. The PRP procedure appears to concentrate dual-task interference on RT2. Theories of the PRP address these effects primarily. The controversy between them concerns interactions of difficulty factors and SOA within and between tasks (see McCann & Johnston, 1992; Meyer & Kieras, 1997a, 1997b; Pashler, 1989; Pashler & Johnston, 1989; Schumacher et al., 1999; Van Selst & Jolicoeur, 1997).

Telford (1931) was the first to coin the term *psychological refractory period.* He had subjects perform a simple RT task to

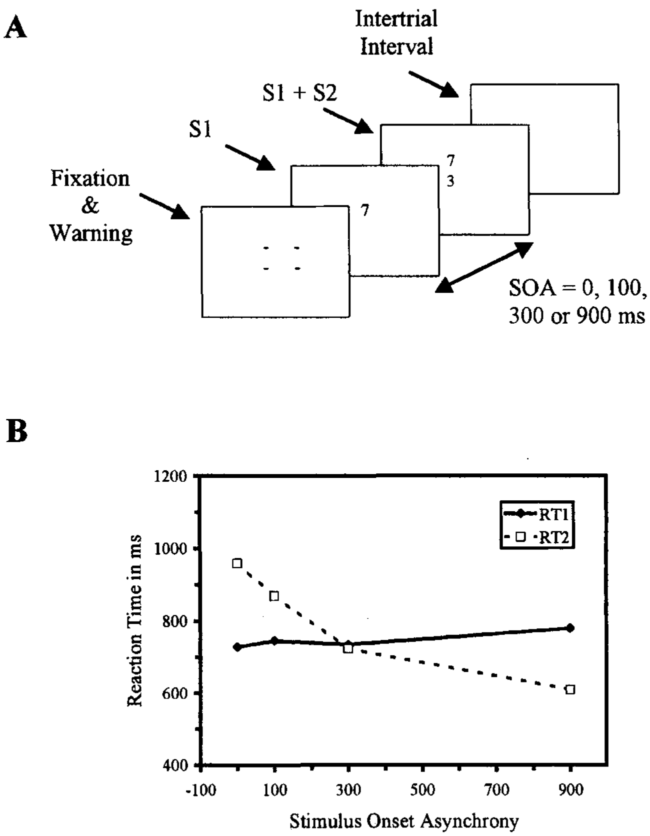

Figure 1. Example of typical procedure (Panel A) and results (Panel B) in a psychological refractory period experiment. S1 is the digit 7, which is the first stimulus; S2 (second stimulus) is the digit 3, which appears below S1; SOA = stimulus onset asynchrony; RT1 = reaction time for response S1; RT2 = RT for response to S2.

"sounds" presented with various intervals between them (500, 1,000, 2,000, and 4,000 ms). He found that subjects were slowest when the interval was shortest, and he argued that the response to the first stimulus put the person in a state of psychological refractoriness, analogous to the refractory state of neurons after they produce an action potential. Vince (1948) and Welford (1952) developed procedures more like the current ones. They used shorter intervals and found more slowing of RT2, which they interpreted in terms of queuing for access to central processes rather than refractoriness. Despite the change in interpretation, Telford's term persists.

It is possible that the first theory in modern cognitive psychology was Welford's (1952) *single-channel* theory of the PRP. Inspired by Craik (1947, 1948) and adopted and expanded by Broadbent (1957, 1958), it became a general theory of attention that influenced the first generation of cognitive psychologists and every one that followed. The core idea was that every deliberate response to a stimulus passed through a *central bottleneck* stage that could deal with only one thing at a time. Around 1970, *capacity* or *resource* theories arose as alternatives to single-channel theory, and they too addressed the PRP and related paradigms (Kahneman, 1973; McLeod, 1977; Posner & Boies, 1971). In the 1980s, resource theory declined (Allport, 1980; Navon, 1984), particularly as an explanation of the PRP (Pashler, 1984, 1994b).

Current Theories of the PRP

Response selection bottleneck. In 1984, Pashler resurrected a form of single-channel theory, casting it in terms of processing stages defined theoretically by a simple rational analysis and empirically by patterns of interaction and additivity among difficulty factors affecting RT (Pashler & Johnston, 1989; Schweickert, 1978; Schweickert & Townsend, 1989; Townsend & Schweickert, 1989). Response selection bottleneck (RSB) theory assumes that performance on each task is based on a series of processing stages that extend from stimulus to response. One of the stages is a bottleneck in the sense that it can do only one thing at a time. Processing in stages prior to the bottleneck can go on in parallel with another task, but processing in the bottleneck stage is dedicated to one task at a time. Many experiments converged on the conclusion that response selection was the locus of the bottleneck, so the theory came to be known as *response selection bottleneck* theory (DeJong, 1993; McCann & Johnston, 1992; Pashler, 1984, 1989, 1991; Pashler & Johnston, 1989; Van Selst & Jolicoeur, 1997; but see Schumacher et al., 1999).

Strategic response deferment. Meyer and Kieras (1997a, 1999) developed an architecture called *executive process interactive control* that accounts for many executive phenomena in the attention literature (also see Meyer et al., 1995). In 1997, they developed the *strategic response deferment* (SRD) model within this architecture and applied it to detailed results in the PRP literature (Meyer & Kieras, 1997a, 1997b). SRD provides precise quantitative accounts of many PRP phenomena (Meyer & Kieras, 1997b). It differs sharply from RSB in two critical respects. First, SRD assumes there is no central bottleneck, so RT2 slowing at short SOAs is strategic, whereas RSB assumes the central bottleneck is a structural property of the cognitive system, so RT2 slowing is unavoidable. Second, SRD assumes that PRP phenomena result from scheduling and control strategies enacted by a central executive, whereas RSB theory says nothing about such strategies and explains PRP phenomena without them.[1] ECTVA is more like SRD than RSB in these two respects. ECTVA assumes that executive processes play important roles in PRP phenomena and that RT2 slowing is strategic—subjects choose to respond serially because TVA works better in series than in parallel.

Relations among ECTVA, RSB, and SRD. ECTVA can be viewed in two ways. From one perspective, it may be an elaboration of certain processes in RSB and SRD. ECTVA provides a specific computational account of stimulus and response selection stages that are part of RSB and SRD. From another perspective, ECTVA may be an alternative theory that competes with RSB and SRD, providing an account of PRP phenomena that differs from

[1] Of course RSB theorists are aware of executive effects in the PRP (e.g., Pashler, 1994a), but the theorists' awareness is not the issue. Rather, the issue is the constructs that the theorists include in their theories, and RSB theories do not include executive scheduling and control strategies in their explanations of PRP phenomena.

their accounts in significant ways. At this point, we prefer the first perspective. We want to use ECTVA to explore certain executive effects in the PRP task, and that exploration should inform research with RSB and SRD. The second perspective may be an interesting one to pursue in future research. It would require a different research agenda, focusing on the data sets that RSB and SRD address, which concern the locus of the bottleneck, if there is one, rather than the executive effects that interest us.

Executive Control of TVA

In creating TVA, Bundesen (1990) said "no attempt is made to discard the notion that attentional selection is controlled by an intelligent agent, but a serious attempt is made to relieve the burden on the agent by placing a powerful mechanism at its disposal" (p. 523). Our theory takes advantage of Bundesen's mechanism, placing it at the disposal of an executive process that controls its parameters. In TVA, performance depends on several parameters, some of which are determined by the stimulus situation and some of which are controlled by Bundesen's intelligent agent. In our theory, a task set is precisely the set of *control parameters* that is necessary to program TVA to perform a particular task. Task sets differ from each other in terms of the number of control parameters they require and the values the control parameters take. In order to distinguish between the executive processes and the subordinate processes they control, we refer to the executive part of our theory as ECTVA and the subordinate part of our theory as *TVA*. ECTVA is specified more abstractly than TVA. In terms of Marr's (1982) levels of analysis, we specify TVA at the computational and algorithmic levels, whereas we specify ECTVA at only the computational level. We say what computations ECTVA must perform to control TVA, but we do not provide algorithms that perform those computations.

A sketch of the ECTVA architecture is presented in Figure 2. We provide a computational account of some of the black boxes underlying performance—those concerned with stimulus selection (TVA) and response selection (EBRW)—but we say nothing about the others. We assume an early perceptual stage that encodes stimuli into a form addressable by TVA, and we assume a later motor stage that turns a symbolic representation of the response into an overt action. Like RSB, we assume that the early perceptual stage can be shared by two or more tasks and that this parallelism is responsible for underadditive interactions between SOA and stimulus contrast and intensity (DeJong, 1993; Pashler, 1984; Pashler & Johnston, 1989).

We assume that task sets are represented in two different systems, working memory and TVA, at two different levels, the *task level* and the *parameter level.* The task-level representation is held in working memory and not in TVA. It is a propositional representation of the task instructions that specifies the appropriate task set for the subject. The parameter-level representation is a set of TVA control parameters that were derived from the propositional representation. It resides in working memory and, once it has been transmitted, it also resides in TVA as a set of instantiated parameters. Once ECTVA transmits the control parameters to TVA, the task-level representation may be represented more compactly in working memory, as a single chunk or a set of chunks, or it may be allowed to decay because it can be retrieved quickly from long-term memory. At this point, we are more concerned with the interaction between working memory and TVA than with the fate of the propositional representation of the task set in working memory.

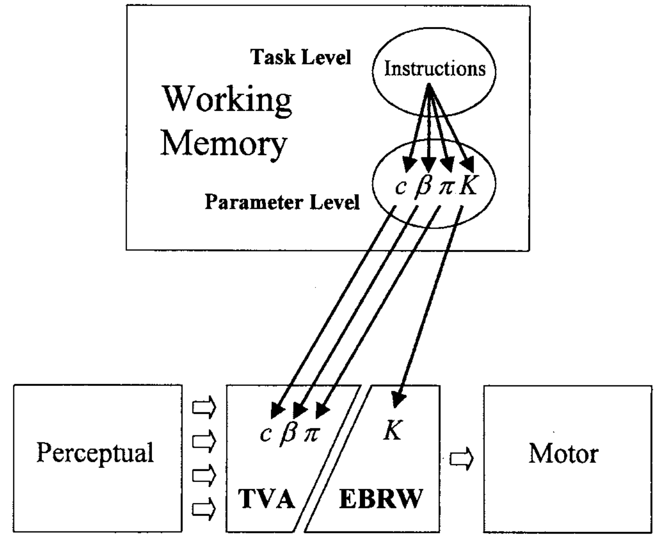

Figure 2. Depiction of the basic architecture of the executive control of visual attention (ECTVA) theory. Boxes represent processing stages; perceptual and motor stages are discrete; theory of visual attention (TVA) and exemplar-based random-walk (EBRW) stages are cascaded. Working memory contains two representations of the task, one at the task level and one at the parameter level. ECTVA passes parameters from working memory to TVA.

In our theory, establishing a task set involves passing a set of control parameters from working memory to TVA, and switching task sets involves deriving a new set of control parameters in working memory and passing them to TVA. Transmitting control parameters is one of two major executive functions in our theory. The other executive function is to reset evidence-accumulation processes after a response to prevent perseveration and enable the next response. We are interested primarily in the time required to switch sets, and we assume that depends on the number of parameters to be changed. TVA allows us to enumerate the control parameters required for a given task set and therefore to make precise predictions about set switching times. The enumeration of control parameters is strongly constrained by the structure of TVA. The control parameters must be sufficient to allow TVA to perform the task, producing RTs and accuracies like human subjects.

We assume that the task-level representation is hierarchical, with the higher level specifying the order in which the tasks occur and the lower level specifying each task separately. The lower level chunks are translated into TVA parameters, which are transmitted to TVA. Alternatively, we could assume that the task-level representation is not hierarchical and does not represent the order of tasks explicitly. Task order depends entirely on stimulus order; first come, first served. DeJong (1995) conducted a series of experiments to distinguish between these alternatives, and his results favored hierarchical representation.[2]

We assume the task-level representation is hierarchical, but we do not make much use of this assumption in our simulations. We focus primarily on the time required to transmit a parameter-level representation of the task set from working memory to TVA. Some of the details of the hierarchical representation have been addressed in other work (e.g., Logan, 1995; Logan & Zbrodoff, 1999).

TVA

TVA is a powerful theory with broad scope. Bundesen and his colleagues developed it to account for a wide range of performance in partial- and whole-report tasks (Bundesen, 1987; Bundesen, Pedersen, & Larsen, 1984; Bundesen, Shibuya, & Larsen, 1985; Duncan et al., 1999; Shibuya & Bundesen, 1988). Bundesen (1990) extended the theory to account for single item identification, position cuing, feature search, and priority learning (also see Bundesen, 1998a, 1998b). Logan (1996) combined TVA with the *COntour DEtector* (CODE) theory of perceptual grouping by proximity (Compton & Logan, 1993, 1999; Van Oeffelen & Vos, 1982, 1983) to form the *CODE theory of visual attention* (CTVA), which accounts for a variety of distance and grouping effects in search and attention tasks, including illusory conjunctions and the Eriksen and Eriksen (1974) flanker task. Logan and Bundesen (1996) applied CTVA to distance and grouping effects in partial report. Logan (2001) related TVA formally to Nosofsky's (1984, 1986, 1988) *generalized context model* of classification (GCM) and Nosofsky and Palmeri's (1997; also see Palmeri, 1997) EBRW model of speeded classification, which provide quantitative accounts of an impressive range of phenomena in the categorization literature. TVA can be configured in a way that mimics the structure of GCM or EBRW exactly, so in principle it can account for the same categorization phenomena as GCM and EBRW. Thus, TVA accounts for a broad range of cognitive phenomena within and beyond the attention literature. Its success in so many domains encouraged us to try to extend it to dual-task and executive-processing phenomena.

ECTVA uses a version of TVA that is extended to include a random-walk response selection process. This version of TVA is really TVA combined with Nosofsky and Palmeri's (1997) EBRW theory. TVA samples the display and categorizes the samples it takes. The categorizations accumulate in *response counters* that are part of the random-walk response selection process. When the number of counts in one of the counters exceeds a criterion (i.e., when it has K more counts than any other counter) the response associated with that counter is chosen and executed. This combination of TVA and EBRW is quite powerful, predicting a broad range of RT and accuracy effects. The combination is already in the literature (see Bundesen & Harms, 1999; Logan, 1996, 2001; Nosofsky & Palmeri, 1997). The novel contribution of ECTVA lies in specifying how this version of TVA can be controlled to produce dual-task behavior. As we shall see, not much needs to be added to TVA and EBRW to account for dual-task phenomena. TVA has been explained several times in the literature (see Bundesen, 1990, 1998a, 1998b; Duncan et al., 1999; Logan, 1996, 2001; Logan & Bundesen, 1996). We explain it again in a manner slightly different from previous explanations to make clear how we use it in ECTVA.

Attention as choice. The most basic assumption in TVA is that attention is a choice process (Bundesen, 1998a, 1998b; Logan, 2001). The stimuli in the display (members of the display set **D**) compete to be classified as members of a set of response categories (as members of the response set **R**). Selection occurs when an object in the display is assigned to a category in the response set. The object and the category are chosen at the same time in a single act of apprehension. The choice process itself involves a race among the competing alternatives. The runner that finishes first is selected, or the first several runners to finish may be selected. TVA assumes that each runner in the race is represented by an independent exponential distribution of finishing times that is characterized by a rate parameter, v (for *velocity*). The rate parameter $v(x, i)$ represents the rate at which the categorization "x is i" runs in the race. The probability of choosing categorization i for object x is given by the ratio of the rate parameter for "x is i" to the sum of the rate parameters for all possible categorizations in the response set (i.e., all categories $j \in \mathbf{R}$) for all possible objects in the display (i.e., all objects $z \in \mathbf{D}$):

$$P(\text{“}x \text{ is } i\text{”}) = \frac{v(x, i)}{\sum_{z \in D} \sum_{j \in R} v(z, j)}. \tag{1}$$

Because the finishing-time distributions for the runners are exponential and stochastically independent, the finishing-time distribution for the winner of the race is also exponential with a rate parameter equal to the sum of the rate parameters of all the runners in the race (Townsend & Ashby, 1983). The mean finishing time for the race, T_{first}, is given by

$$T_{first} = \frac{1}{\sum_{z \in D} \sum_{j \in R} v(z, j)}. \tag{2}$$

[2] DeJong (1995) presented subjects with auditory and visual stimuli in a PRP procedure and allowed the order of stimuli in the dual-task trials to vary randomly. On some trials, task order repeated (e.g., visual–auditory followed by visual–auditory). On other trials, it alternated (e.g., visual–auditory followed by auditory–visual). DeJong argued that the contrast between repeated and alternating task order distinguished hierarchical representation from a first-come, first-served strategy. The hierarchical view represents order explicitly and so should benefit from repetitions of task order (because that aspect of the task representation does not have to be changed when task order repeats). It also predicts a tendency to repeat the task order from the previous trial, so that subjects may respond to S2 before S1 if task order alternates and SOA is brief. By contrast, the first-come, first-served view does not represent task order explicitly and so does not predict benefit from task-order repetitions. It predicts faster performance when task order alternates (e.g., visual–auditory followed by auditory–visual) because there are fewer set switches (one between S1 and S2 but none between S2 and the following S1). DeJong's data supported the hierarchical view: Subjects were faster when task order repeated than when it alternated. When task order alternated and SOA was brief (100 ms), subjects often responded in the same order as on the previous trial, responding to S2 before S1.

The rate parameters, v, depend on a combination of parameters that represent the stimulus situation and the task set. To explain the nature of the parameters and the way they are combined, it is useful to begin with the choice of a category for a single object and follow with the complications that arise with several objects in the display. Those complications include binding objects to categorizations and resolving perceptual interference from nearby objects. After dealing with multiple objects, we introduce the assumptions about response selection and their interaction with TVA. At that point, we will be done with the background and ready to proceed with the new theory (ECTVA) that specifies how TVA is controlled in dual-task situations.

Categorizing one object. If there is only one object (x) in the display, the rate at which a categorization (i) is selected—that is, the rate parameter, $v(x, i)$—depends on the *similarity* between the object and a representation of the response category (i.e., a prototype or a set of exemplars) and the subject's *bias* toward selecting objects in the response category. The similarity between object x and category i is given by $\eta(x, i)$ (η for *evidence*). The greater the similarity, the larger the value of η. The bias for category i is given by β_i (β for *bias*); the greater the bias, the larger the value of β. The rate parameter $v(x, i)$ is the product of the evidence parameter and the bias parameter:

$$v(x, i) = \eta(x, i)\beta_i. \tag{3}$$

Equation 3 can be substituted into Equations 1 and 2 to give choice probabilities and finishing times for single-object categorization. The expression that results from substituting Equation 3 into Equation 1,

$$P(\text{“}x \text{ is } i\text{”}) = \frac{\eta(x, i)\beta_i}{\sum_{j \in R} \eta(x, j)\beta_j}, \tag{4}$$

is known as the *Shepard–Luce choice rule* (Luce, 1963; Shepard, 1957). It has a venerable history, having been used in a large number of mathematical models for 40 years. Marley and Colonius (1992) and Bundesen (1993) have shown that independent race models, such as TVA, were equivalent to a large class of Shepard–Luce choice models, in that a race model could be constructed to mimic the choice probabilities of a given Shepard–Luce model. This equivalence broadens the scope of TVA substantially and relates it formally to a large number of models (see Logan, 2001).

The evidence parameter η is not determined by the homunculus. It is determined by the stimulus properties of the object x and by the subject's history with members of category i. The bias parameter β is determined by the homunculus. It is one of the four parameters ECTVA uses to control TVA. It is part of the parameter-level representation of the task set (see Figure 2).

Evidence and bias combine multiplicatively in Equation 4. Consequently, only objects with high η and high β have a chance to be selected. Objects with low η or low β or both are unlikely to be selected. The multiplication allows β to act as a gain control so ECTVA can "turn up" desired categorizations and "turn down" undesired ones. The choice of which βs to set high (i.e., the decision about the composition of the response set **R**) corresponds to *response set* (Broadbent, 1971) or *analyzer selection* (Treisman, 1969) in classical analyses of attention.

To illustrate the interaction of η and β, consider a case in which the digit 7 is presented on a screen and the subject's task is to determine its magnitude, that is, to decide whether it is greater than 5 or less than 5. ECTVA turns a propositional representation of these instructions into two β parameters, β_{large} for digits greater than 5 and β_{small} for digits less than 5 (e.g., setting both "high" to 1), and passes these parameters to TVA. When the stimulus appears (the object x), perceptual processes create η values for all possible categorizations. This is the function of the perceptual encoding stage in Figure 2. If x is the digit 7, $\eta(x, large)$ would be higher than $\eta(x, small)$ (e.g., 10 and 1, respectively), and $\eta(x, odd)$ would be higher than $\eta(x, even)$ (e.g., 10 and 1, respectively). However, the task is to discriminate magnitude, so ECTVA sets β high (e.g., to 1) for magnitude judgments and low (possibly to 0) for parity (odd–even) judgments. Consequently, only $\eta(x, large)$ and $\eta(x, small)$ enter the choice competition. In the example, the probability of choosing "large" when given the digit 7 is $\eta(x, large)\beta_{large}/[\eta(x, large)\beta_{large} + \eta(x, small)\beta_{small}] = (10 \times 1)/[(10 \times 1) + (1 \times 1)] = 0.909$ (see Equation 4), and the choice would be made in $1/[(10 \times 1) + (1 \times 1)] = 0.091$ units of "model time" (see Equations 2 and 3).

Categorizing two objects: The binding problem. Introducing a second object, y, into the display complicates the choice process. The probability of choosing category i for object x is

$$P(\text{“}x \text{ is } i\text{”}) = \frac{\eta(x, i)\beta_i}{\sum_{j \in R} \eta(x, j)\beta_j + \sum_{j \in R} \eta(y, j)\beta_j} \tag{5}$$

Equation 5 shows that the impact of the second object depends on its similarity to the categories in the response set. If y is very dissimilar to the categories in the response set, $\Sigma\ \eta(y, j)$ would approach 0, and $P(\text{“}x \text{ is } i\text{”})$ would be almost the same as in the single-object case; Equation 5 would approximate Equation 4. However, if y is very similar to the categories in the response set, $\Sigma\ \eta(y, j)$ could equal or exceed $\Sigma\ \eta(x, j)$, and $P(\text{“}x \text{ is } i\text{”})$ could drop below 0.5. For example, if the response set for x was "large or small digits" and y was a green disk, choice probabilities for x would not be affected much, but if y was the digit 3, choice probabilities for x would be affected strongly; y would be as likely to be chosen as x. If correct performance depended on responding to x, this level of accuracy would be unacceptable in most RT experiments. In the example above, assuming that the digit 3 produces $\eta(y, large) = 1$ and $\eta(y, small) = 10$, the probability of choosing "large" for the digit 7 would be $(10 \times 1)/[(10 \times 1) + (1 \times 1) + (1 \times 1) + (10 \times 1)] = 0.455$.

The problem introduced by a similar second object is known as the *binding problem:* Given two objects and a categorization, how does the executive system know from which object the categorization came (Hummel & Biederman, 1992; Pylyshyn, 1989; Treisman & Gelade, 1980; Ullman, 1984)? The first categorization to be chosen is likely to be a correct categorization of one of the two objects, but without further information the executive system has no way to know which object goes with which category.

TVA solves the binding problem by introducing a second way to choose among objects, through a priority parameter, π (π for *priority*), that represents the importance of selecting objects that contain one of the properties in the stimulus set **S**. The idea is to choose among objects on the basis of properties that are not in the response set and to use this choice to direct attention to the target object. For example, when given a display of two digits, TVA might give priority to the top digit, setting π_{top} high (e.g., to 1) and π_{bottom} low (e.g., to 0.1), allowing the top digit to be chosen instead of the bottom one. This kind of selection by prioritizing is known as *stimulus set* (Broadbent, 1971) and *input selection* (Treisman, 1969) in classical analyses of attention. It solves the binding problem by allowing the system to attribute categorizations that come out of TVA to the stimulus that was currently prioritized; if "large" comes out of TVA in the example, the system could attribute it to the top object, which was prioritized.

The priority parameter operates in the same manner as the bias parameter, acting as a gain control by multiplying evidence parameters. The products of priority parameters and evidence parameters are summed over the stimulus set **S** for each object to produce an *absolute attention weight.* The absolute attention weight on object x, w_x, is given by

$$w_x = \sum_{k \in S} \eta(x, k)\pi_k. \tag{6}$$

The probability of selecting an object by stimulus set, $P_\pi(x)$, depends on the *relative attention weight* given to the object. The relative attention weight given to object x is the ratio of the absolute attention weight for object x to the sum of absolute attention weights for all objects z in the display **D**:

$$P_\pi(x) = \frac{w_x}{\sum_{z \in D} w_z} = \frac{\sum_{k \in S} \eta(x, k)\pi_k}{\sum_{z \in D}\sum_{k \in S} \eta(z, k)\pi_k}. \tag{7}$$

The summation over the stimulus set **S** in Equations 6 and 7 expresses the general case in which there are several properties in the stimulus set. In typical experiments, there is only one property in the stimulus set (e.g., "top" in the previous example). Strayer (1997) examined performance in a visual search task with several properties in the stimulus set, manipulating the number of properties that distinguished the target from the distractors. He found that search RT decreased as the number of properties in the stimulus set increased, confirming a TVA prediction (Bundesen, 1990).

The priority parameter, like the bias parameter, is determined by the homunculus.[3] It is one of the control parameters of TVA and part of the parameter-level representation of the task set in ECTVA. The evidence parameter on which it operates is determined by the stimulus situation and the subject's history with members of the relevant category, just like the evidence parameter on which the bias parameter operated. The difference between stimulus set and response set is functional rather than structural. The property that is selected by stimulus set in one task may be selected by response set in another. For example, in a display with the digit 7 above the digit 3, one task set might be to select the top object (stimulus set) and report its magnitude (response set), while another task set might be to select the large digit (stimulus set) and report its location (response set; for further discussion of stimulus set and response set in TVA, see Logan, 2001).

Consider the example of selecting the top digit. If object x is the top digit, then $\eta(x, top)$ would be high (e.g., 10), and $\eta(x, bottom)$ would be low (e.g., 1). Object y is the bottom object with $\eta(y, top)$ low (e.g., 1) and $\eta(y, bottom)$ high (e.g., 10). ECTVA sets π_{top} high (e.g., 1) to select the top digit and π_{bottom} low (e.g., 0.1) to avoid selection of the bottom digit. Following Equation 7, the probability of selecting the top digit would be $[(10 \times 1) + (1 \times 0.1)]/[(10 \times 1) + (1 \times 0.1) + (1 \times 1) + (10 \times 0.1)] = 0.835$.

The probability of selecting an object by stimulus set combines with the probability of choosing a categorization by response set by multiplication: Each η value for a response set category is multiplied by the relative attention weight on the object to which it refers and that is given by stimulus set. Thus, processing rate becomes

$$v(x, i) = \eta(x, i)\beta_i \frac{w_x}{\sum_{z \in D} w_z}, \tag{8}$$

the probability of choosing category i for object x becomes

$$P(\text{"}x \text{ is } i\text{"}) = \frac{\eta(x, i)\beta_i \frac{w_x}{\sum_{z \in D} w_z}}{\sum_{z \in D}\sum_{j \in R} \eta(z, j)\beta_j \frac{w_z}{\sum_{z \in D} w_z}}, \tag{9}$$

and the finishing time for the first categorization becomes

$$T_{first} = \frac{1}{\sum_{z \in D}\sum_{j \in R} \eta(z, j)\beta_j \frac{w_z}{\sum_{z \in D} w_z}}. \tag{10}$$

In the example above, in which the digit 7 appears on top, the digit 3 appears on the bottom, and the task is to categorize the magnitude of the top digit, the probability of calling the top digit "large" would be $(10 \times 1 \times 0.835)/[(10 \times 1 \times 0.835) + (1 \times 1 \times 0.835) + (1 \times 1 \times 0.165) + (10 \times 1 \times 0.165)] = 0.878$. Response set by itself produced an accuracy of 0.455 (see Equation 5). Combining stimulus set and response set, as TVA does, increases accuracy considerably.

Perceptual constraints. Single-task performance is strongly affected by the proximity and perceptual organization of objects in the display. Logan (1996) and Logan and Bundesen (1996) addressed these effects by combining TVA with the CODE theory of perceptual grouping by proximity (Compton & Logan, 1993, 1999;

[3] Bundesen (1990) assumed that π was driven partly by the environment and partly by the subject. He assumed that π changed during the course of priority learning (i.e., learning where to look or what to look for in a display; see Shiffrin & Schneider, 1977). We prefer to interpret priority learning in terms of changes in η values that π multiplies in determining attention weights (see Equations 6 and 7) rather than in terms of π (also see Logan, 2001). That leaves π under the control of the executive and η under the control of the subject's history with the environment. Future research will be necessary to distinguish Bundesen's view from ours.

Van Oeffelen & Vos, 1982, 1983) to form CTVA. CTVA assumes that objects are distributed over representational space so that focusing attention on a region in the display results in a sampling of the features of several objects, with objects closer to the region contributing more to the sample. Perceptual organization depends on the overlapping distributions of object features, and those distributions determine the regions that attention can address and sample features from.

The details of CODE and CTVA are not necessary for the purposes of this article (but see Bundesen, 1998b; Logan, 1996; Logan & Bundesen, 1996). Suffice it to say that CODE provides TVA with a *feature-catch* parameter, c_x, that ranges between 0 and 1 and represents the proportion of the features of x that are available ("caught") in the current perceptual organization of the display. CTVA incorporates the feature-catch parameter into TVA by multiplying each evidence parameter by the appropriate value of c. Processing rate becomes

$$v(x, i) = c_x \eta(x, i) \beta_i \frac{w_x}{\sum_{z \in D} w_z}, \tag{11}$$

absolute attention weight becomes

$$w_x = \sum_{k \in S} c_x \eta(x, k) \pi_k, \tag{12}$$

the probability of choosing "x is i" becomes

$$P(\text{“}x \text{ is } i\text{”}) = \frac{c_x \eta(x, i) \beta_i \frac{w_x}{\sum_{z \in D} w_z}}{\sum_{z \in D} \sum_{j \in R} c_z \eta(z, j) \beta_j \frac{w_z}{\sum_{z \in D} w_z}}, \tag{13}$$

and the finishing time for the first categorization becomes

$$T_{first} = \frac{1}{\sum_{z \in D} \sum_{j \in R} c_z \eta(z, j) \frac{w_z}{\sum_{z \in D} w_z}} \tag{14}$$

The value of c depends partly on the stimulus situation and partly on the homunculus. It depends on the stimulus situation because it depends on the proximity of the objects to the sampled region, and that is determined by the spatial arrangement of objects in the stimulus display. It depends on the homunculus because the homunculus chooses among alternative perceptual organizations of the display and among perceptual groups within the display (see Logan, 1996); c is part of the parameter-level representation of the task set.

In our application of TVA to ECTVA we set $c = 1$ for both of the objects in the display. Strictly speaking, ECTVA includes TVA rather than CTVA, but the generalization to CTVA is straightforward should it be useful in future research.

Response Selection (EBRW)

We model response selection with Nosofsky and Palmeri's (1997; also see Palmeri, 1997) EBRW theory. We assume that TVA works continuously as long as input is present (i.e., as long as $\eta > 0$) and β and π are set high. Technically, the race in TVA is a Poisson process that keeps running at the same rate, producing categorizations with probabilities defined in Equation 13 at a rate equal to the reciprocal of Equation 14. We assume that the response selection process works concurrently with TVA and that its processing is contingent on TVA's output (cf. Turvey, 1973). Thus, TVA and response selection are cascaded stages rather than discrete stages (Ashby, 1982; McClelland, 1979). TVA's output—categorizations of perceptual objects—is accumulated in a response selection process that consists of several counters and a difference threshold, K. We assume there is one counter for each response and that a perceptual categorization from TVA increments the counter that corresponds to it. Typically, there is one counter for each distinct β value in TVA, but more complex mapping rules could be implemented. Each time a counter increments, the difference threshold is applied. If the number of counts in one counter exceeds the largest number of counts in the other counters by K, then response selection terminates, and the response corresponding to the above-threshold counter is executed.

If K is set to 1.0, then response selection terminates as soon as TVA provides the first categorization. If K is 1.0, response selection can be characterized as an *independent race model* (e.g., Bundesen, 1993; Logan, 1988; Strayer, 1997). If K is set to a value greater than 1.0, several categorizations may accumulate before one counter exceeds the others by K. If K is greater than 1.0, response selection can be characterized as a *random-walk model* (Nosofsky & Palmeri, 1997; Palmeri, 1997). The race model is a special case of the random-walk model with $K = 1.0$. Alternatively, the random-walk model is a generalization of the race model to values of K greater than 1.0 (Nosofsky & Palmeri, 1997).

The ability to set K to a value greater than 1.0 allows EBRW to maintain an acceptable level of accuracy when the accuracy of individual categorizations is less than perfect (Nosofsky & Palmeri, 1997; Palmeri, 1997). Individual categorizations may be less than perfectly accurate because the stimulus is weak (so η is small), the display is crowded (so c is small), the alternative categories are similar to each other (so $\eta/\Sigma\ \eta$ is small), or there is conflict from distracting stimuli (e.g., in the flanker task). If $K = 1.0$, response selection terminates as soon as the first categorization finishes, and accuracy is defined by Equation 13. If the individual categorizations are less than perfect, the first categorization will often be wrong. Setting K greater than 1.0 provides some insurance against these quick errors. Subsequent runners in the race can override the influence of the first erroneous categorization so that the response is ultimately correct. If there are two alternatives, accuracy can be made arbitrarily high by setting K accordingly, as long as the correct response is more probable than the incorrect one. The random walk must take more steps as K increases, so RT and accuracy both increase with K. This is how random-walk models account for the speed–accuracy tradeoff (Ratcliff, 1978, 1988).

We assume that K is controlled by the homunculus. ECTVA uses it to control the speed and accuracy of response selection. It is part of the parameter-level representation of the task set (see Figure 2). Following Nosofsky and Palmeri (1997; Palmeri, 1997), the time taken for each step of the random walk is

$$T_{Step} = T_{first} + \alpha = \frac{1}{\sum_{z \in D} \sum_{j \in R} v(z, j)} + \alpha, \quad (15)$$

where the first term on the right-hand side is the time taken for the race, given by Equation 14, and the second term, α, is the time required to increment the counter and compare counter values against the difference criterion, K. RT is the sum of the T_{Step} values defined in Equation 15 over the number of steps required for the random walk to terminate. Analytic solutions for the expected number of steps (RT) and accuracy are available if there are only two response alternatives (e.g., in Nosofsky & Palmeri, 1997). Our application to the PRP procedure requires four responses (two for each task), so we had to simulate the random walk.

We chose to model response selection as a random walk because random-walk models have provided good accounts of a variety of RT and accuracy data and the relation between them (see, e.g., Ratcliff, 1978, 1988; Townsend & Ashby, 1983). We chose the EBRW version because EBRW is very similar to TVA formally (see Logan, 2001). Both assume a Poisson process that produces similarity-based categorizations at a rate that is influenced by a bias parameter. EBRW differs from TVA in providing no attention weights (i.e., the ws in Equations 13 and 14) and in providing no feature-catch parameters (i.e., the cs in Equations 13 and 14). However, EBRW "unpacks" the similarity parameter η, defining it in terms of distance between stimuli in multidimensional similarity space, whereas TVA treats it as an atomic entity (so far; but see Logan, 2001).

Parameters, Task Sets, and Identifiability

To summarize, the single-task version of TVA has six kinds of parameters: c, η, π, β, K, and α. One, η, depends on the stimulus situation and the subject's history rather than the subject's homunculus. Another, α, represents a fixed cost of incrementing the counters and testing the threshold in response selection. The other four—c, π, β, and K—are under the subject's control. They give Bundesen's (1990) "intelligent agent" control over the "powerful mechanism" of TVA. In our theory, these four subject-controlled parameters constitute a task set. They comprise the parameter-level representation of the task set that ECTVA derives from the task-level chunk and passes to the subordinate process, TVA. As we shall see, ECTVA adds two more parameters: one that describes the mean time required to transmit TVA parameters from working memory to TVA and one that describes the amount by which the values in the response counters are reduced after a response (see *Serial Order Problem* and *Set-Switching Costs* sections).

Fitting the single-task version of TVA to a data set can involve a large number of parameters. Usually, there is only one value of K and one value of α. There is one c parameter for each object and each perceptual group. There are β parameters for each categorization in the response set **R** and π parameters for each property in the stimulus set **S**. There are η parameters for each combination of perceptual object and categorization. A model with so many parameters would appear to have a lot of flexibility.

In practice, there are constraints on the parameters that reduce the number required, and Equations 11–14 constrain the interactions among the parameters. Parameter c is a probability, so it ranges from 0 to 1.0. It is also constrained by the spatial arrangement of the display (see Logan, 1996). Parameters β and π usually range from 0 to 1.0, although in principle they could take any positive value. Typically, all of the βs for desired categorizations are set to the same value and all of the πs for desired stimulus properties are set to the same value. K is usually greater than 1.0 but less than 5.0 or so. It must be greater than 1.0 to prevent fast errors, but it does not need to be much more than 1.0 to produce accuracy of 90% or higher. The η parameters can be constrained in several ways. Nosofsky (1984, 1986, 1988) has often fixed their values by constructing a multidimensional similarity space for the set of stimuli he uses in his experiments. The η values are then determined by distances in multidimensional similarity space. They are no longer free to vary to optimize fit.

We restricted the number of free parameters in our fits to the data sets, fixing the values of some parameters and choosing one of two values of other parameters to turn them on and off rather than to optimize fit to the data sets. We manipulated η, β, and π, and we fixed c, K, and α. The ηs were set to 10 for matching categorizations and to 1 for mismatching categorizations; β and π were both set to 1.0 for desired categorizations and to 0.1 for undesired categorizations; c was fixed at 1.0, so it dropped out of Equations 1 and 2; K was fixed at 3.0 because this was the smallest value that produced reasonable accuracy; and α was fixed at 0.3 throughout. We chose these restrictions on the parameters and their values in order to show that the effects follow from the structure of the model (i.e., Equations 11–14) and not the parameter values. Our goal was not to explain all systematic variance in PRP data but rather to explain certain effects of executive processing in terms of ECTVA (see Hintzman, 1991).

Executive Control in the PRP Procedure: Running TVA Twice

So far, we have described the application of TVA to single-task situations. The novel contribution of ECTVA is to apply TVA to dual-task situations, specifically to the PRP procedure. ECTVA deals with the PRP procedure by running TVA twice, once on S1 and once on S2. In order to run TVA twice, ECTVA has to solve two problems that emerge in dual-task situations: the dual-task binding problem (Hummel & Biederman, 1992; Pylyshyn, 1989; Treisman & Gelade, 1980; Ullman, 1984) and the serial order problem (Lashley, 1951). These problems can be solved by having the executive manipulate mechanisms that are already part of TVA.

Dual-Task Binding Problem

In the PRP situation there are two stimuli, S1 and S2, and two responses, R1 and R2. The dual-task binding problem lies in figuring out which response goes with which stimulus. TVA solved the single-task binding problem with stimulus set. It gave priority to one of the objects, making it more likely to be selected than the other. Consequently, categorizations that emerged from TVA and responses that emerged from EBRW could be attributed to the prioritized object. ECTVA uses stimulus set to solve the binding problem in dual-task situations by giving priority to S1 and S2 in series. ECTVA sets π high for S1 until R1 emerges and then sets π high for S2 to select R2. The categorizations that emerge from TVA and the responses that emerge from EBRW are attributed to S1 when S1 has priority and to S2 when S2 has priority.

TVA's stimulus-set solution to the binding problem would not work if both S1 and S2 were given priority at the same time. If S1 and S2 were prioritized in parallel, S2 would be as likely as S1 to be categorized first in TVA and generate the first response in EBRW. There would be no way to know which response goes with which stimulus; the binding problem would remain. Some other method could be developed to solve it, but that method would require mechanisms beyond those found in TVA. ECTVA recommends serial processing as the solution to the binding problem, because it is more parsimonious. It can be done with the stimulus set mechanism that is already part of TVA.

The serial stimulus-set solution to the binding problem creates a need for executive processes that change stimulus set from Task 1 to Task 2. Similar executive processes would be required to change other parameters when other aspects of the task set change from Task 1 to Task 2 (e.g., response set). We introduced these processes earlier, as ones that transmit the parameter-level representation of the task set from working memory to TVA (see Figure 2). We address the time course of these processes in the *Set-Switching Costs* section.

Serial Order Problem

The PRP procedure requires two responses: R1 and R2. The first response (R1) can be chosen with the usual response selection process—EBRW. The counters accumulate categorizations until one has K more than any other, and the response associated with that counter is selected. The serial order problem concerns what happens next: How is the second response chosen? If EBRW remains in the same state it was in when R1 was selected, R1 will continue to have K more categorizations than any other counter, and R1 will be chosen again and again, perseveratively. R2 would never be chosen. Something must be done to reset the response counters to disable R1 and enable R2.

The need to reset the response-selection processes to prevent perseveration has been apparent for a long time in models that account for Lashley's (1951) classical problem of serial order in behavior. Models of serial order generally assume that response order is determined by the activation of alternative responses, such that the most active alternative is chosen (Bryden, 1967; Dell, Burger, & Svec, 1997; Estes, 1972; MacKay, 1987; Rumelhart & Norman, 1982). Once the most active alternative is selected, it must be inhibited or it will be chosen again, perseveratively. The inhibition makes its activation lower than the next highest alternative so the next highest alternative can be chosen in the next cycle and the next response in the sequence can be executed.

To prevent R1 perseveration in the PRP procedure we assume that ECTVA inhibits the random-walk counters after R1 was chosen, reducing them to some percentage of their values. This inhibition reduces the difference between the largest and next-largest counter to a value less than K and that enables choice of R2. The amount by which the counters are inhibited is a parameter of the model that we fixed at 90% in our simulations. In principle, it could vary over a broad range and still prevent R1 perseveration (see *ECTVA, Present and Future*). We assume that the act of inhibition takes time. In our simulations we fixed the time it takes, setting it equal to the time required to change a TVA parameter (see *Set-Switching Costs*).

Advantages of Serial Processing

RSB and SRD agree that subjects usually respond serially in the PRP procedure, but they disagree fundamentally on the reasons for the seriality. RSB assumes that serial processing is obligatory because response selection is an unavoidable bottleneck in processing; serial response selection is the basic axiom of RSB (Pashler, 1984; Pashler & Johnston, 1989). SRD assumes that serial processing is strategic. In principle, subjects could select responses in parallel, but they choose to select them serially to comply with instructions or demand characteristics (Meyer & Kieras, 1997a, 1997b). ECTVA is more like SRD. It can be configured to process S1 and S2 in series or in parallel, and the choice between them is strategic. In this section we report simulations that compare serial and parallel versions of ECTVA in dual-task situations to evaluate the relative advantages.

RSB and SRD differ in their assumptions about capacity limitations in central processes. RSB assumes that response selection is sharply limited in capacity (Pashler, 1984; Pashler & Johnston, 1989) and that other central processes may be limited in capacity as well (Jolicoeur, 1998, 1999a, 1999b; Pashler, 1991). SRD assumes no central capacity limitations in the processing stages underlying the PRP task (Meyer & Kieras, 1997a, 1997b). ECTVA assumes there are two sorts of central capacity limitations: one inherited from TVA and the other inherited from EBRW. Our simulations evaluate the effects of these limitations on the efficacy of serial and parallel processing.

TVA's capacity is defined in terms of the effects of load on processing rate, $v(x, i)$ (Bundesen, 1990; Townsend & Ashby, 1983). Capacity is *unlimited* if $v(x, i)$ does not change when another object is added to the display; capacity is *limited* if $v(x, i)$ decreases when another object is added to the display, and capacity is limited and *fixed* if $v(x, i)$ decreases when another object is added to the display but the sum of the processing rates over all objects in the display **D** is constant (i.e., fixed). By this definition, TVA is limited in capacity. The capacity limitation occurs because processing rates are influenced by relative attention weight (defined in Equation 11) rather than absolute attention weight (defined in Equation 12). Equation 11 is reproduced here for convenience. Relative attention weight is computed by dividing the absolute attention weight on object x by the sum of the attention weights over all objects z in the display **D**:

$$v(x, i) = c_x \eta(x, i) \beta_i \frac{w_x}{\sum_{z \in D} w_z}.$$

If another object is added to the display, its weight enters the denominator of this expression. That decreases the relative weight on object x and consequently slows the processing rates for all categorizations of object x. Capacity is not fixed, however, because $\eta(x, i)$ and β_i are not affected by other objects in the display: $\sum\sum v(z, j)$ is not constant.

We implemented the standard limited-capacity version of TVA using Equation 11 to define processing rates. We implemented a new unlimited-capacity version of TVA by replacing the relative attention weights in Equation 11 with absolute attention weights that were not divided by the sum of all the attention weights:

$$v(x, i) = c_x\eta(x, i)\beta_i w_x = c_x\eta(x, i)\beta_i \sum_{j\in S} c_x\eta(x, j)\pi_j. \quad (16)$$

Processing rate defined by Equation 16 is unlimited in capacity because its value does not depend on the number of objects in the display (cf. Equation 11).

The capacity limitations in response selection (EBRW) stem from the parameter α, which represents the cost of incrementing the random-walk counters and testing the difference threshold, K (see Equation 15). This cost increases the time required for each step of the random walk, and that makes RT depend on the number of steps required to choose a response. If there were no cost of incrementing the counters and testing the difference threshold, RT could be independent of the number of random-walk steps. For example, if TVA and EBRW were both unlimited in capacity, parallel processing may double the rate at which TVA produces categorizations but require twice as many random-walk steps as serial processing; speeding up TVA may compensate for the additional random-walk steps. We manipulated capacity limitations in response selection by varying α. In the standard version of EBRW, response-selection capacity was limited; α was set to 0.3. In the unlimited-capacity version, α was set to 0.0.

We conducted eight simulations, formed by the factorial combination of serial versus parallel processing, TVA capacity limited versus unlimited, and EBRW capacity limited ($\alpha = 0.3$) versus unlimited ($\alpha = 0$). K was fixed at 3.0. There were four parallel models and four corresponding serial models. The parallel models differed from the serial ones only in the π values. In parallel processing, π was set to 1.0 for both S1 and S2 during Task 1 and Task 2. In serial processing, π was set to 1.0 for S1 and 0.1 for S2 during Task 1, and then it was set to 0.1 for S1 and 1.0 for S2 during Task 2. In all other respects, the corresponding models were the same. We did not implement the time required for ECTVA to change TVA parameters or to reset the EBRW counters in these simulations, and we set the counters to 0 after R1. At this point, we wanted to address the effects of capacity limitations on serial and parallel processing without additional complications. We address the additional complications later. Details of the present simulations are described in Appendix A.

The mean RTs from the simulations appear in Figure 3. RT1 was faster than RT2 in each case. RT1 was faster in the serial version than in the parallel version whenever TVA capacity or EBRW capacity was limited. When TVA capacity and EBRW capacity were both unlimited, RT1 was no faster in the serial version than in the parallel version. RT2 was faster in the serial version than in the parallel version whether or not TVA and EBRW capacities were limited. These results suggest a strategic advantage for serial processing whenever capacity is limited.[4]

The accuracy results from the simulations appear in Figure 4. The results show near-ceiling accuracy in each case of serial processing and near-chance accuracy in each case of parallel processing. The parallel-processing results occurred because we took response order into account when we scored accuracy. R1 was scored correct only if it was the appropriate response to S1; R2 was scored correct only if it was the appropriate response to S2. TVA nearly always chose the correct response for each stimulus, but in parallel processing the response to S2 was as likely to finish before the response to S1 as after it. When we scored accuracy irrespective of response order, it was near ceiling in the parallel-processing simulations.

These accuracy results reflect the dual-task binding problem (Hummel & Biederman, 1992; Treisman & Gelade, 1980; Ullman, 1984). Serial processing solves the binding problem naturally: The first response to be selected goes with S1, because TVA was set to process S1 before S2. Parallel processing provides no solution to the binding problem. Other things equal (i.e., η, β, and π equal), R1 is just as likely to follow R2 as to precede it. In principle, some other process could be added to the parallel model to solve the binding problem, but that would increase, not reduce, the RT cost involved in parallel processing. The advantage of serial processing would remain.

The mean numbers of steps required for the random walk to finish appear in Figure 5. In each case, the serial version requires fewer steps than the parallel version. This is a consequence of the difference threshold, K. In serial processing the correct response to S1 has no strong competitors, so it accumulates K more counts than the next highest alternative relatively quickly. By contrast, in parallel processing the correct response to S1 has to compete with the correct response to S2 as well as with their weaker, incorrect responses. It takes longer to accumulate K more counts than a strong alternative than to accumulate K more counts than a weak alternative.

Mean RT was affected by capacity limitations in TVA and EBRW, but accuracy and the number of random-walk steps was not. This follows because accuracy and number of random walk steps depend only on the choice probabilities, given by Equation 13, and not on the time TVA takes to select each categorization or the time it takes to increment the random walk. The choice probabilities are the same whether TVA capacity is limited or unlimited. Choice probabilities are calculated with relative attention weights (Equation 11) when capacity is limited and with absolute attention weights (Equation 16) when capacity is unlimited. Relative attention weights differ from absolute attention weights by a denominator that represents the sum of absolute attention weights over all the objects in the display. This denominator appears in the numerator and denominator of the expression for choice probabilities (Equation 13) and consequently cancels out. This can be seen in Equation 13, which is repeated here:

[4] ECTVA involves two stages, TVA and the random-walk process, in cascade. TVA capacity limitations affect the first stage, and α affects the second. The effects of manipulating TVA capacity limitations and α confirm our two-stage assumption. In the serial simulations, the main effect of TVA capacity was 52 ms, and the main effect of α was 188 ms, but the interaction contrast between these effects was 0 ms. In the parallel simulations, the main effect of TVA capacity was 107 ms, the main effect of α was 373 ms, and the interaction contrast was -3 ms. Variables that affect different stages in a cascade process produce additive effects (Ashby, 1982; McClelland, 1979), so TVA capacity limitations and α affect different stages.

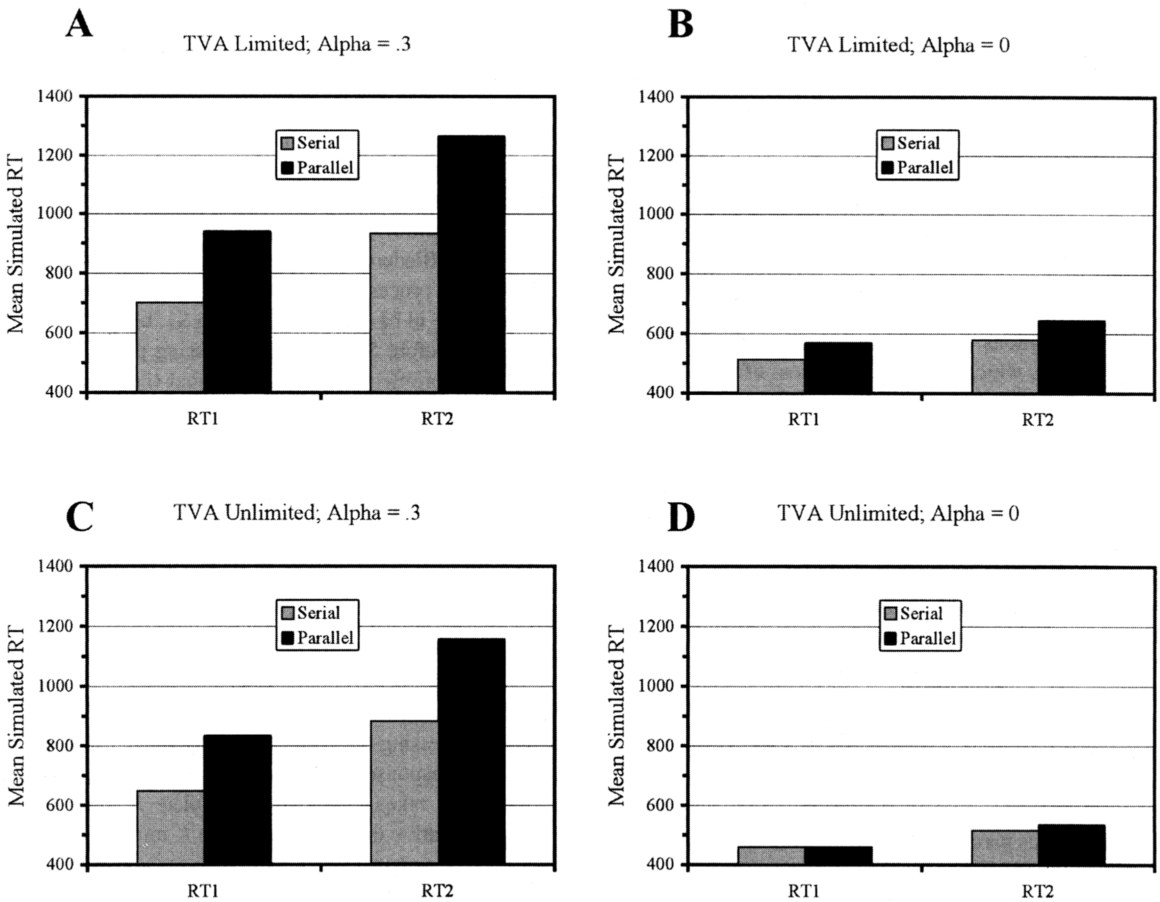

Figure 3. Mean simulated Reaction Times 1 (RT1) and 2 (RT2) from serial and parallel versions of the executive control of visual attention theory. In Panel A, theory of visual attention (TVA) capacity is limited, and so is response-selection capacity; in Panel B, TVA capacity is limited, but response-selection capacity is unlimited; in Panel C, TVA capacity is unlimited, but response-selection capacity is limited; and in Panel D, both TVA and response selection are unlimited in capacity.

$$P(\text{"}x \text{ is } i\text{"}) = \frac{c_x \eta(x, i)\beta_i \dfrac{w_x}{\sum_{z \in D} w_z}}{\sum_{z \in D}\sum_{j \in R} c_z \eta(z, j)\beta_j \dfrac{w_z}{\sum_{z \in D} w_z}} = \frac{c_x \eta(x, i)\beta_i w_x}{\sum_{z \in D}\sum_{j \in R} c_z \eta(z, j)\beta_j w_z}.$$

The middle term is the expression for choice probabilities with relative attention weights, and the rightmost term is the expression for choice probabilities with absolute attention weights. The equation shows the choice probabilities are equivalent. By contrast, RT depends only on the denominator of Equation 13 and so is faster the larger the sum of processing rates. The sum of processing rates is larger when capacity is unlimited than when it is limited as long as the sum of the attention weights is greater than 1 (i.e., $\Sigma\, w_z > 1.0$):

$$T_{first} = \frac{1}{\sum_{z \in D}\sum_{j \in R} c_z \eta(z, j)\beta_j \dfrac{w_z}{\sum_{z \in D} w_z}} > \frac{1}{\sum_{z \in D}\sum_{j \in R} c_z \eta(z, j)\beta_j w_z}.$$

The middle term represents finishing time with relative attention weights, and the rightmost term represents finishing time with absolute attention weights. The expression shows they are not equivalent. RT also depends on the time required to increment the random-walk counter and test the difference threshold (i.e., α in Equation 15), and that time is independent of accuracy.

To summarize, the simulations showed a strong advantage of serial processing over parallel processing in RT whenever capacity was limited and a strong advantage in accuracy and the number of random-walk steps whether or not capacity was limited. Consequently, we chose to run TVA serially in the remaining simulations. ECTVA is like SRD and unlike RSB in that it assumes that serial processing is a strategic choice. In ECTVA the strategic choice is motivated by the performance of TVA in parallel and in serial configurations. Serial processing is advantageous because it is faster and more accurate and because it provides a natural solution to the dual-task binding problem.

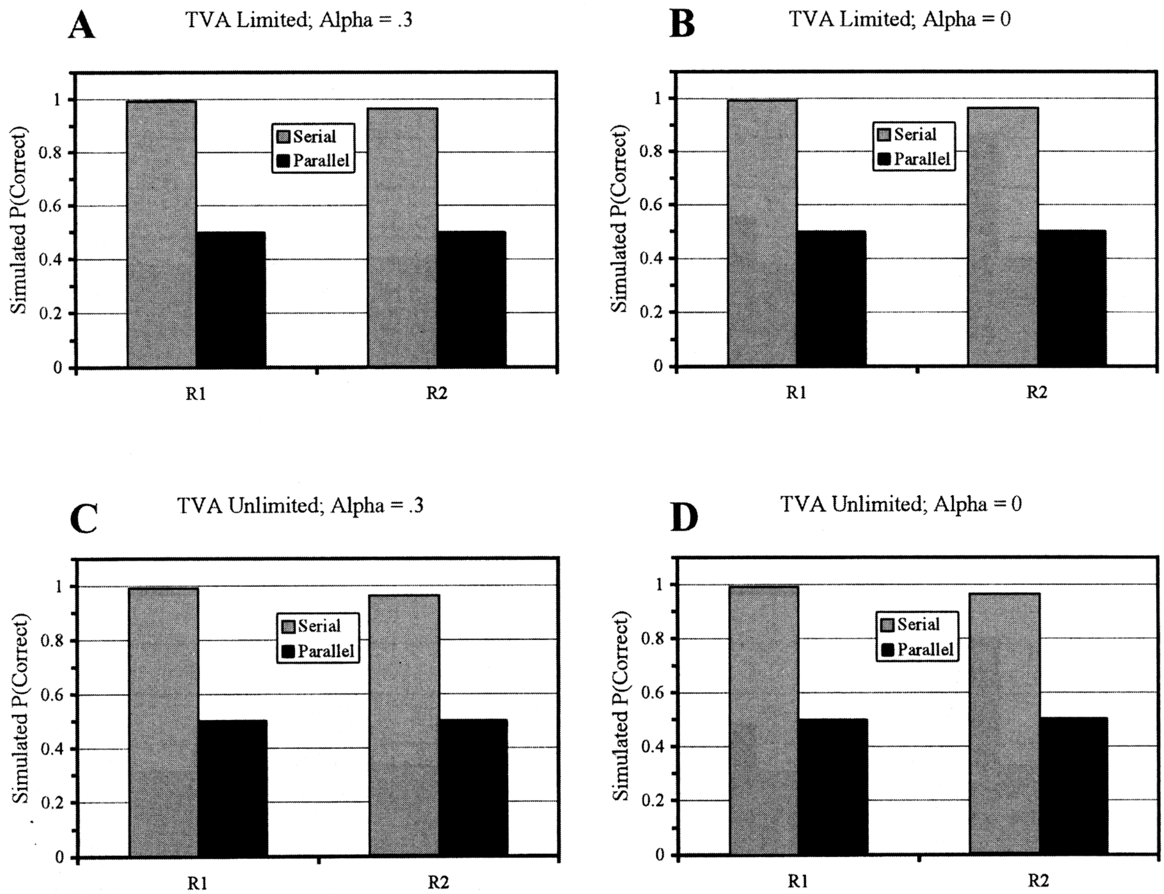

Figure 4. Simulated accuracy for Responses 1 and 2 (R1 and R2) from serial and parallel versions of the executive control of visual attention theory. In Panel A, theory of visual attention (TVA) capacity is limited, and so is response-selection capacity; in Panel B, TVA capacity is limited, but response-selection capacity is unlimited; in Panel C, TVA capacity is unlimited, but response-selection capacity is limited; and in Panel D both TVA and response selection are unlimited in capacity.

Effects of Executive Processing

In theory, executive processes coordinate and control subordinate processes (Logan, 1985; Meyer & Kieras, 1997a, 1997b; Norman & Shallice, 1986). Empirically, executive processes are identified with several effects that emerge when two or more operations must go on at once or when two or more tasks must go on at once (Duncan, 1979). These effects generally cannot be explained in terms of subordinate processes, so executive processes must be invoked. We consider three such effects—crosstalk, set-switching costs, and concurrence costs—and see how ECTVA explains them. It turns out that the machinery we have described so far is sufficient to account for these effects: Crosstalk and the dependence of crosstalk on task set is explained in terms of β, which is part of TVA. We have to add an assumption that separate βs can be assigned to S1 and S2, but otherwise the TVA machinery is sufficient. Set-switching costs are explained in terms of the time it takes to change parameters and the number of parameters that need to be changed, which reflect the part of ECTVA that makes TVA run serially. Concurrence costs are explained in terms of set-switching time and in terms of response competition in EBRW.

Crosstalk

The term *crosstalk* refers to informational interference between one communication channel and another. Crosstalk is a common feature of our daily dual-task experience. For example, it is hard to follow a tune on television when the person next to you is playing a different tune on the guitar. Crosstalk is a popular topic in psychological research. Many researchers examine crosstalk in single-task situations in which distractor stimuli (Eriksen & Eriksen, 1974) or distracting attributes (Stroop, 1935) impair RT to the target stimulus or stimulus attribute. Crosstalk is also found between tasks in dual-task situations. Between-task crosstalk occurs when the stimuli from one task are relevant to the task set for the other task, and consequently influence how the other task is performed. For example, Navon and Miller (1987) had subjects decide whether the word in one location was a boy's name and at the same time decide whether the word in another location was a

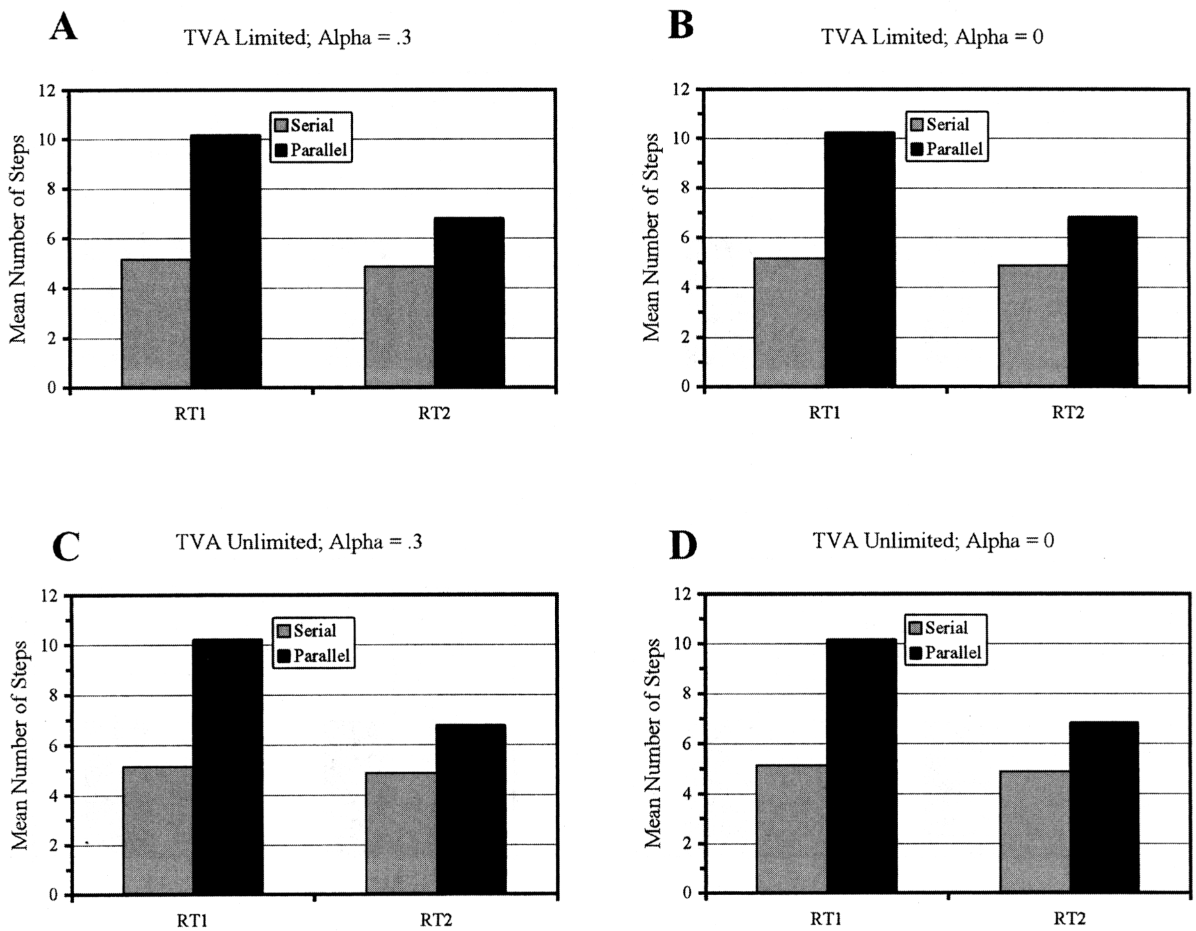

Figure 5. Mean simulated number of random-walk steps underlying Reaction Times 1 (RT1) and 2 (RT2) from serial and parallel versions of the executive control of visual attention theory. In Panel A, theory of visual attention (TVA) capacity is limited, and so is response-selection capacity; in Panel B, TVA capacity is limited, but response-selection capacity is unlimited; in Panel C, TVA capacity is unlimited, but response-selection capacity is limited; and in Panel D both TVA and response selection are unlimited in capacity.

city name. When the distractors for the city name task were boys' names, subjects were substantially slower on the boys' names task, as if information from the city-name task "leaked through" (also see Hirst & Kalmar, 1987).

Several researchers have found crosstalk between tasks in PRP situations (Duncan, 1979; Hommel, 1998; Logan & Delheimer, in press; Logan & Schulkind, 2000). For example, Logan and Schulkind (2000, Experiment 2) presented subjects with two digits with an SOA of 0–900 ms between them. Task 1 and Task 2 were both magnitude judgments (was the digit larger than 5 or smaller than 5). RT1 and RT2 were both faster if S1 and S2 were both large or both small (i.e., if the categorizations were *congruent*) than if one was large and the other was small (i.e., if the categorizations were *incongruent*). The effect of S2 categorization on RT1 is a clear example of between-task crosstalk. It indicates that Task 2 categorization processes were active at the same time as Task 1 categorization processes. The processes cannot have been discrete and serial (Logan & Delheimer, in press; Logan & Schulkind, 2000; also see Townsend & Ashby, 1983).

Crosstalk between tasks depends on overlap between the task sets for Task 1 and Task 2. Logan and Schulkind (2000) examined the dependence of crosstalk on task set in a PRP experiment in which S1 and S2 were both digits. Subjects performed magnitude judgments (greater than or less than 5) or parity judgments (odd or even) on them. Subjects experienced all four combinations of task (parity or magnitude) and stimuli (S1 or S2), producing two same-task-set conditions (magnitude–magnitude and parity–parity) and two different-task-set conditions (magnitude–parity and parity–magnitude). The data showed strong between-task crosstalk effects only in the same-task-set conditions. When task set was different, there was no crosstalk. Thus, crosstalk appears to depend on a common task set.

Overlap in stimulus properties is neither necessary nor sufficient to produce crosstalk. Logan and Schulkind (2000) found no crosstalk when the task sets were different even though S1 and S2 were both digits and so overlapped in stimulus properties. Hommel (1998) found crosstalk with no overlap in stimulus properties. He had subjects report the color and the location of a disk with overlapping response categories. In his first experiment, subjects reported location by pressing a left or right key and color by saying "left" for red and "right" for green. He found strong crosstalk effects under these conditions. In subsequent experiments he had subjects report color by pressing keys and location by saying "red" and "green" and found strong crosstalk again.

ECTVA and perceptual crosstalk. Three different mechanisms that are already part of ECTVA can produce crosstalk in dual-task situations. One mechanism, implemented primarily in CTVA, is the feature-catch parameter, c. If a distractor object is sufficiently close to a target, features of the distractor will be "caught" in the sample of features taken from the target. Those distractor features will be interpreted in terms of the task set (i.e., the set of β values) that is applied to the target and may facilitate performance if the interpretation is consistent with the target or impair performance if the interpretation is inconsistent with the target. Logan (1996) used this idea to account for the effects of distractor congruity and proximity in Eriksen and Eriksen's (1974) flanker task.

Perceptual crosstalk produced by the feature-catch parameter cannot be modulated by task set, as the crosstalk observed in Logan and Schulkind's (2000) experiment was modulated. The features "caught" at the target location are analyzed in terms of the target's task set regardless of the task set (if any) applied to the distractors. Consequently, we decided not to implement perceptual crosstalk in our attempt to model our PRP crosstalk effects. We set c to 1.0 for S1 and S2—we simulated TVA instead of CTVA. That removed perceptual crosstalk and simplified the equations.

ECTVA and category-level crosstalk. The second kind of crosstalk is a consequence of the stimulus-set or serial-processing solution to the binding problem: ECTVA attributes all categorizations to the stimulus that is currently given priority. The model does not know explicitly whether a given categorization came from S1 or S2 (see Logan, Taylor, & Etherton, 1999), but it makes an attribution based on the assumption that the categorization is likely to have come from the currently prioritized object. If priority is high for S1, then categorizations of S2 count in choosing a response to S1. If priority is high for S2, then categorizations of S1 count in choosing a response to S2. The probability of incrementing an EBRW counter depends on the probability of categorizing both S1 and S2 as members of that category. Formally, we defined categorization probabilities in terms of the following equation:

$$\begin{aligned} P(\text{“}x \text{ is } i\text{”}) &= P(\text{“S1 is } i\text{”}) + P(\text{“S2 is } i\text{”}) \\ &= \frac{v(\mathrm{S1},i)}{\sum_{j\in R} v(\mathrm{S1},j) + \sum_{j\in R} v(\mathrm{S2},j)} \\ &\quad + \frac{v(\mathrm{S2},i)}{\sum_{j\in R} v(\mathrm{S1},j) + \sum_{j\in R} v(\mathrm{S2},j)} \\ &= \frac{v(\mathrm{S1},i) + v(\mathrm{S2},i)}{\sum_{j\in R} v(\mathrm{S1},j) + \sum_{j\in R} v(\mathrm{S2},j)}, \end{aligned} \tag{17}$$

rather than in terms of Equation 13. This crosstalk occurs at the category level rather than the perceptual level. Categorizations are confused. Perceptual evidence for the categorizations is not confused.

To understand how Equation 17 produces crosstalk, consider a concrete example presented in Figure 6. There are two stimuli, S1 and S2, presented one above the other. S1 is on top. Each stimulus is a digit and has two dimensions—magnitude and parity—and each dimension has two possible values: large or small for magnitude and odd or even for parity. Let us focus first on crosstalk from S2 to S1, which occurs during Task 1. We assume that S1 is 7, so it is large and odd. This is represented in TVA by four η values: $\eta(S1, large)$, which is set to 10.0; $\eta(S1, small)$, which is set to 1.0; $\eta(S1, odd)$, which is set to 10.0; and $\eta(S1, even)$, which is set to 1.0. Task 1 is to discriminate magnitude, so β_{large} and β_{small} are set high (to 1.0), and β_{odd} and β_{even} are set low (0.1). Processing is serial, so π_{top} is set high (1.0) to select S1, and π_{bottom} is set low (0.1) to exclude S2.

Processing rates for each categorization of S1 are determined by multiplying η, β, and π values. For example, $v(S1, large)$ is computed by multiplying $\eta(S1, large)$ by β_{large} and multiplying that value by the product of $\eta(S1, top)$ and π_{top}, which represents the attention weight on S1.[5] The results of this multiplication for the four possible categorizations of S1 appear in Figure 6. The processing rate for "large" (i.e., $v[S1, large]$) is higher than any other, so S1 is likely to be classified as large.

The middle and bottom panels of Figure 6 show the processing rates for S2. The middle panel shows the congruent case, in which S2 is 9 so it is categorized the same as S1 (i.e., large and odd), sharing the same values of the two dimensions. Consequently, the η values are the same as for S1: high for large and odd and low for small and even. We assume that the task set is the same for S2 as for S1, so β_{large} and β_{small} are set high, and β_{odd} and β_{even} are set low. Processing is serial, so π_{bottom} is low, to exclude S2. The processing rates for the four possible categorizations appear in Figure 6. They are lower overall than the processing rates for S1, but they show the same pattern: Like S1, S2 is most likely to be categorized as large. The processing rates for S1 and S2 add together to produce response probabilities (Equation 17), and that increases the likelihood of categorizing S1 as large. Consequently, RT1 will be facilitated, and R1 accuracy will be high.

The bottom panel of Figure 6 contains the incongruent case, in which S2 is 3. It differs from S1 in the relevant dimension (i.e., magnitude). The pattern of η values is reversed: $\eta(S2, large)$ is now 1.0, and $\eta(S2, small)$ is now 10.0. The task set is the same as in the congruent case, and processing is still serial, so the β and π values remain the same. The processing rates for S2 remain lower than the processing rates for S1, but now the pattern is different. S2 is more likely to be categorized as small than large, and this conflicts with the categorization of S1. When the processing rates for S1 and S2 are added together (Equation 17), the probability of categorizing S1 as large is not enhanced, as it was in the congruent

[5] To simplify Figure 6, we assumed capacity was unlimited, so the attention weight $\eta(S1, top)\pi_{top}$ would not have to be divided by the sum of the attention weights on S1 and S2. We also ignored $\eta(S1, bottom)\pi_{bottom}$ in the calculation. Its value would have been negligible (i.e., $1.0 \times 0.1 = 0.1$) and so could be ignored. Note that we did not use these simplifications in our simulations of ECTVA.

Crosstalk From S2 to S1

S1 = 7 in top position

				η	β	η	π	v
$v(S1,large)$	=	$\eta(S1,large)\beta_{large}\ \eta(S1,top)\pi_{top}$	=	10.0 x	**1.0** x	10.0 x	1.0 =	**100.0**
$v(S1,small)$	=	$\eta(S1,small)\beta_{small}\ \eta(S1,top)\pi_{top}$	=	1.0 x	**1.0** x	10.0 x	1.0 =	**10.0**
$v(S1,odd)$	=	$\eta(S1,odd)\beta_{odd}\ \eta(S1,top)\pi_{top}$	=	10.0 x	**0.1** x	10.0 x	1.0 =	**10.0**
$v(S1,even)$	=	$\eta(S1,even)\beta_{even}\ \eta(S1,top)\pi_{top}$	=	1.0 x	**0.1** x	10.0 x	1.0 =	**1.0**
							Σv =	121.0

Congruent: S2 = 9 in bottom position

				η	β	η	π	v
$v(S2,large)$	=	$\eta(S2,large)\beta_{large}\ \eta(S2,bottom)\pi_{bottom}$	=	10.0 x	**1.0** x	10.0 x	0.1 =	**10.0**
$v(S2,small)$	=	$\eta(S2,small)\beta_{small}\ \eta(S2,bottom)\pi_{bottom}$	=	1.0 x	**1.0** x	10.0 x	0.1 =	**1.0**
$v(S2,odd)$	=	$\eta(S2,odd)\beta_{odd}\ \eta(S2,bottom)\pi_{bottom}$	=	10.0 x	**0.1** x	10.0 x	0.1 =	**1.0**
$v(S2,even)$	=	$\eta(S2,even)\beta_{even}\ \eta(S2,bottom)\pi_{bottom}$	=	1.0 x	**0.1** x	10.0 x	0.1 =	**0.1**
							Σv =	12.1
							$\Sigma\Sigma v$ =	133.1

P("x is large") = (100 + 10)/133.1 = **.826**
P("x is small") = (10 + 1)/133.1 = .083
P("x is odd") = (10 + 1)/133.1 = .083
P("x is even") = (1 + 0.1)/133.1 = .008

Incongruent: S2 = 3 in bottom position

				η	β	η	π	v
$v(S2,large)$	=	$\eta(S2,large)\beta_{large}\ \eta(S2,bottom)\pi_{bottom}$	=	1.0 x	**1.0** x	10.0 x	0.1 =	**1.0**
$v(S2,small)$	=	$\eta(S2,small)\beta_{small}\ \eta(S2,bottom)\pi_{bottom}$	=	10.0 x	**1.0** x	10.0 x	0.1 =	**10.0**
$v(S2,odd)$	=	$\eta(S2,odd)\beta_{odd}\ \eta(S2,bottom)\pi_{bottom}$	=	10.0 x	**0.1** x	10.0 x	0.1 =	**1.0**
$v(S2,even)$	=	$\eta(S2,even)\beta_{even}\ \eta(S2,bottom)\pi_{bottom}$	=	1.0 x	**0.1** x	10.0 x	0.1 =	**0.1**
							Σv =	12.1
							$\Sigma\Sigma v$ =	133.1

P("x is large") = (100 + 1)/133.1 = **.759**
P("x is small") = (10 + 10)/133.1 = .150
P("x is odd") = (10 + 1)/133.1 = .083
P("x is even") = (1 + 0.1)/133.1 = .008

Figure 6. Executive control of visual attention theory (ECTVA) account of crosstalk. The top panel presents ECTVA response to Stimulus 1 (S1), the middle panel presents ECTVA response to S2 when S1 and S2 are congruent, and the bottom panel presents ECTVA response to S2 when S1 and S2 are incongruent. Note that the processing rates, v, are determined by two η values. The first one represents the similarity between the stimulus and the to-be-reported category in the response set (determined by β), and the other represents the similarity between the stimulus position and the position that is given priority (determined by π) in the stimulus set.

case. Rather, the probability of categorizing S1 as small is enhanced, resulting in an increase in RT1 and a decrease in R1 accuracy.

ECTVA explains crosstalk from S2 to S1 during Task 1 with one mechanism, the source confusion that results from attributing all categorizations to the currently prioritized object (i.e., Equation 17). ECTVA explains crosstalk from S1 to S2 during Task 2 with two mechanisms. One is the category-level mechanism just described, and the other is a response-level mechanism, described below. Computing category-level crosstalk from S1 to S2 requires changing the π values so that π_{top} is low, to exclude S1, and π_{bottom} is high, to select S2. Otherwise, the processing rates can be computed in the same way as in Figure 6. If S1 and S2 are congruent, RT2 will be facilitated and R2 accuracy will be higher.

ECTVA and response-level crosstalk. The third ECTVA mechanism for producing crosstalk lies in the inhibition of the random-walk counters. Once R1 is chosen, ECTVA inhibits the values in the random-walk counters to prevent perseveration of R1. Our simulations reduce the counter values by 90%. This incomplete inhibition produces crosstalk from R1 to R2. It leaves a "trace" of S1 in the counters, and the trace biases EBRW to respond to S2 in the same way it responded to S1. If S2 is the same as S1 or congruent with it, fewer counts will be needed to categorize S2 correctly, and RT2 and R2 accuracy will be facilitated. If S2 is different from S1 or incongruent with it, more counts will be needed to respond to S2 correctly, and RT2 and R2 accuracy will be impaired. We discuss the relation between the amount by which the counters are inhibited and the amount of crosstalk later (see *ECTVA, Present and Future*).

Set-Switching Costs

In daily life, people switch between tasks as often as they do two tasks at once. A task performed alone can seem more difficult if it is preceded and followed by other demanding tasks, as many parents can attest. Psychologists have become quite interested in switching between tasks in recent years, although the first study was done a long time ago. Jersild (1927) showed that subjects were substantially slower to perform two tasks when they had to alternate between task sets than when they stayed with one task set throughout. This *set-switching cost* has proven to be easy to replicate in a variety of domains and has become a popular topic for research because of what it can reveal about executive control processes (see e.g., Allport et al., 1994; Allport & Wylie, 2000; DeJong, 2000; Meiran, 1996; Rogers & Monsell, 1995).

The typical PRP procedure involves a change in task set from Task 1 to Task 2 (e.g., from tone discrimination to letter discrimination; Pashler & Johnston, 1989), but PRP researchers have not been concerned with set switching or with the interactions it may produce or prevent. Logan and Schulkind (2000) examined set switching in the digit magnitude and parity PRP tasks we just discussed. They found that RT1 and RT2 were both much slower when the task set was different (e.g., Task 1 magnitude, Task 2 parity) than when the task set was the same (both magnitude or both parity), suggesting that set-switching costs play a large role in PRP tasks.

ECTVA on set switching. ECTVA allows us to enumerate the parameters that are necessary to perform several different tasks. This provides us with a formal definition of task set and a definition of a major independent variable affecting set-switching time: the number of parameters to be changed (Dixon, 1981; Rosenbaum, 1980). In our theory, a task set is a set of TVA control parameters (i.e., c, β, π, and K) that is sufficient to produce responses that fulfill the task goals. Whenever the task changes, some control parameters must be changed so that TVA will respond in accord with the new task goals. We assume that several steps are involved in switching set. ECTVA may have to derive the TVA parameters from a propositional representation of the task instructions, and that could take several steps, depending on the complexity of the instructions. Once TVA parameters are derived and placed in working memory, ECTVA transfers them to TVA. We assume that the transfer process takes time, and the time it takes depends on the number of parameters to be changed (Dixon, 1981; Rosenbaum, 1980). We assume that the transmission process is parallel and unlimited in capacity, so the time taken to switch sets depends on the time required to transmit the slowest parameter. That is, we assume that all parameters must be transmitted before TVA starts processing, so the time required to transmit them all is the maximum of the individual transmission times.

We implement set switching by assuming that transmission times are distributed exponentially, all with the same rate parameter. Thus, the time required to switch N parameters is the maximum of N samples from the same exponential distribution. The mean time required to switch N parameters is

$$E(T_{Max}) = \frac{1}{v}\sum_{i=1}^{N}\frac{1}{i}, \tag{18}$$

where v is the rate parameter for the exponential distribution of transmission times (Townsend & Ashby, 1983). It increases as a negatively accelerated function of N. To keep the simulations stochastic, we estimated set-switching time by simulating the transmission process instead of using the mean value (Equation 18). We took N samples from an exponential distribution with a given rate parameter and selected the largest value in the set of samples as the set-switching time for a given trial.

An important step in the ECTVA analysis is determining the number of parameters to be changed. The number of parameters that need to be changed is smallest if the task set is the same for S1 and S2. At minimum, π needs to change to select S2 instead of S1. So one parameter needs to be changed from Task 1 to Task 2. When the next trial begins, we assume that π needs to be changed once more to select S1 instead of S2. So Task 1 also requires one parameter to be changed. The situation is more complicated if the task set changes from Task 1 to Task 2. In addition to resetting π to select S2, several β values need to be changed to instantiate the Task 2 response set in TVA and enable R2 selection in EBRW. At minimum, β for S2 needs to be set high for the categorizations relevant to Task 2.

According to this analysis, RT1 and RT2 should both include a component due to set-switching time. The component should be larger when the task set is different and several parameters have to change than when the task set is the same and only one parameter has to change. We assumed that inhibiting the random-walk counters takes the same time, on average, as transmitting a parameter, and we modeled this by adding one more parameter to the number being transmitted, increasing N in Equation 18 by one unit.

In our theory, the executive responds to states of the subordinate, so we assume that parameter transmission is triggered when ECTVA detects some state in TVA or EBRW or both. We assumed that ECTVA transmits parameters for Task 1 when it notes the onset of S1 in TVA, perhaps through changes in η (from low to high) or when it anticipates S1, predicting its onset from TVA's response to the warning signal. We did not model the detection process in our simulations. We assumed that transmission began with the onset of S1 because it was easy to implement. It was consistent with some claims in the literature that task sets cannot be engaged completely until the relevant stimulus appears (Rogers & Monsell, 1995; Ward, 1982) and with other claims that subjects do not prepare optimally (DeJong, 2000). We assumed that ECTVA began transmitting parameters for Task 2 as soon as EBRW selected R1. When SOA was shorter than RT1, parameter transmission began well after S2 appeared. When SOA was longer than RT1, some or all of the parameters could be transmitted before S2. For details, see Appendixes A and C.

Set switching modulates crosstalk. ECTVA accounts for the modulation of crosstalk by task set by assigning βs separately to S1 and S2. The βs for the task set for Task 1 are assigned to S1, and the βs for the task set for Task 2 are assigned to S2. When the task set is the same for Task 1 and Task 2, the βs are the same, so categorizations of S1 can be confused with categorizations of S2, and vice versa (see Equation 17). There will be crosstalk between S1 and S2. When the task set is different, the βs are different, and the categorizations are not likely to be confusable. Crosstalk between S1 and S2 will be sharply diminished.

The predicted modulation in crosstalk by set switching can be understood more formally by considering the example in Figure 7. Figure 7 shows processing rates for S1 and S2 when the task set is the same or different and Task 1 is underway. As in Figure 6, we assume that S1 and S2 are digits with two dimensions (magnitude and parity) and that each dimension has two values (large vs. small and odd vs. even). S1 is the digit 9 in the top position, and the task set is magnitude judgment. The top panel of Figure 7 presents the η, β, and π parameters for S1. The rate parameters show a strong likelihood of categorizing S1 as large.

The middle and bottom panels of Figure 7 show the processing rates for S2 as a function of the congruency of S1 and S2. The middle panel shows the same-task-set condition. Both Task 1 and Task 2 involve magnitude judgments. The β values for S2 are set high for large and small and low for odd and even, just as they were for S1. The S2 processing rates are higher for magnitude than for parity and so have a strong impact on S1 categorization probabilities.

The bottom panel of Figure 7 shows the different-task-set condition for S2. The task set for Task 2 is parity rather than magnitude. The S2 η and π values are the same as in the same-task-set condition, but the β values are different. They are set low for large and small and high for odd and even, reflecting the different task set. Consequently, the pattern of processing rates is different. Now the S2 processing rates are for low for magnitude and high for parity. When processing rates are added to produce categorization probabilities, following Equation 17, the small processing rates for magnitude have little effect on S1 categorization probabilities. The same considerations apply to Task 2. Categorization probabilities for S2 will be affected more if the task set is the same than if it is different, just as they were for S1.

The idea that βs can be assigned separately to S1 and S2 plays a crucial role in ECTVA's account of the modulation of crosstalk by task set, but it was not part of TVA. It is new to ECTVA. In single-task TVA, βs generally applied to all stimuli in the display (Bundesen, 1990). The dual-task situation creates a need to respond differently to different parts of the display. Indeed, the instructions specify separate task sets—separate discriminations and responses—for S1 and S2, and it seems reasonable that the task sets would be represented separately and associated with the relevant stimuli in ECTVA's task-level representation in working memory (see Figure 2). The additional assumption is that task sets are also represented separately in the parameter-level representation in working memory and TVA.

The idea that βs can be set separately for S1 and S2 implies that βs can be set low as well as high. Our simulations of different-task-set and single-task conditions assume that ECTVA sets βs for S2 low when it is processing S1 and then sets βs for S1 low when it is processing S2. The time required to change these βs contributes to set-switching costs. Our simulations of same-task-set conditions, however, assume that ECTVA sets βs high for both S1 and S2 and keeps them high throughout Task 1 and Task 2 to reduce set-switching time (see Appendices C and G).

Concurrence Costs

In daily life, the contrast between doing two things at once and doing one thing at a time is often particularly salient. When you drive fast in heavy traffic, deep philosophical discussions are out of the question. The contrast between dual-task and single-task performance has been salient in the psychological literature as well. Many dual-task studies contrast performance in dual-task conditions with performance in single-task control conditions and, as in daily life, performance is usually worse in dual-task conditions. This difference is known as *concurrence cost* (Navon & Gopher, 1979). Some portion of the concurrence cost may be due to increased demands for cognitive "resources" or central bottlenecks during dual-task performance, but some other portion appears to be due to the expectation to perform two tasks in the dual-task condition (Logan, 1979, 1980b). Gottsdanker (1979), for example, showed that RT2 was slowed substantially when S1 was expected but did not appear.

Studies of the PRP typically do not include single-task controls. The invariance of RT1 over SOA is taken as evidence that Task 1 received priority and was protected from interference (Pashler, 1994a). This conclusion seems to imply that Task 1 performance would be equivalent to single-task performance. The elevation of RT2 at short SOAs is interpreted as dual-task interference, and the decline in RT2 as SOA increases is assumed (perhaps implicitly) to asymptote at the level of single-task performance on Task 2. Thus, for Task 2, performance at a long SOA can serve as a single-task control for performance at short SOAs.

A few studies have run single-task controls in the PRP procedure. Studies that compared dual-task RT1 with single-task RT generally found slower RTs in the dual-task condition (Bertelson, 1967; Gottsdanker, Broadbent, & Van Sant, 1963; Herman & McCauley, 1969; Hommel, 1998). Other studies compared RT2 in single- and dual-task conditions. RT2 was usually much longer than single-task controls. Although the RT1 effects are important (see, e.g., Herman & Kantowitz, 1970), researchers have focused more on the RT2 effects. For example, Pashler (1984) first worked out his arguments for RSB by contrasting RT2 in dual-task conditions with RT to the same stimulus (and task) in single-task conditions. Later, he and Johnston worked out the arguments in terms of the contrast between RT2 effects at long and short SOAs (Pashler & Johnston, 1989). Since then, most PRP studies have followed Pashler and Johnston's example and compared RT2

Crosstalk Depends on Task Set

S1 = 9, top

		η	β	η	π	v
$v(S1,large)$	$= \eta(S1,large)\beta_{large}\ \eta(S1,top)\pi_{top}$	= 10.0 x	**1.0**	x 10.0 x	1.0 =	**100.0**
$v(S1,small)$	$= \eta(S1,small)\beta_{small}\eta(S1,top)\pi_{top}$	= 1.0 x	**1.0**	x 10.0 x	1.0 =	**10.0**
$v(S1,odd)$	$= \eta(S1,odd)\beta_{odd}\ \eta(S1,top)\pi_{top}$	= 10.0 x	**0.1**	x 10.0 x	1.0 =	**10.0**
$v(S1,even)$	$= \eta(S1,even)\beta_{even}\ \eta(S1,top)\pi_{top}$	= 1.0 x	**0.1**	x 10.0 x	1.0 =	**1.0**
					Σv =	121.0

Same Task Set

		Congruent: S2 = 7 ($\eta\ \beta\ \eta\ \pi\ v$)	*Incongruent:* S2 = 3 ($\eta\ \beta\ \eta\ \pi\ v$)
$v(S2,large)$	$= \eta(S2,large)\beta_{large}\ \eta(S2,bot)\pi_{bot} =$	10 x **1.0** x 10 x 0.1 = **10.0**	1 x **1.0** x 10 x 0.1 = **1.0**
$v(S2,small)$	$= \eta(S2,small)\beta_{small}\ \eta(S2,bot)\pi_{bot} =$	1 x **1.0** x 10 x 0.1 = **1.0**	10 x **1.0** x 10 x 0.1 = **10.0**
$v(S2,odd)$	$= \eta(S2,odd)\beta_{odd}\ \eta(S2,bot)\pi_{bot} =$	10 x **0.1** x 10 x 0.1 = **1.0**	10 x **0.1** x 10 x 0.1 = **1.0**
$v(S2,even)$	$= \eta(S2,even)\beta_{even}\ \eta(S2,bot)\pi_{bot} =$	1 x **0.1** x 10 x 0.1 = **0.1**	1 x **0.1** x 10 x 0.1 = **0.1**
		Σv = 12.1	Σv = 12.1

$\Sigma\Sigma v$ = 133.1

P("x is large")	= (100 + 10)/133.1	= **.826**	(100 + 1)/133.1	= **.759**
P("x is small")	= (10 + 1)/133.1	= .083	(10 + 10)/133.1	= .150
P("x is odd")	= (10 + 1)/133.1	= .083	(10 + 1)/133.1	= .083
P("x is even")	= (1+0.1)/133.1	= .008	(1+0.1)/133.1	= .008

Different Task Set

		Congruent: S2 = 7 ($\eta\ \beta\ \eta\ \pi\ v$)	*Incongruent:* S2 = 3 ($\eta\ \beta\ \eta\ \pi\ v$)
$v(S2,large)$	$= \eta(S2,large)\beta_{large}\ \eta(S2,bot)\pi_{bot} =$	10 x **0.1** x 10 x 0.1 = **1.0**	1 x **0.1** x 10 x 0.1 = **0.1**
$v(S2,small)$	$= \eta(S2,small)\beta_{small}\eta(S2,bot)\pi_{bot} =$	1 x **0.1** x 10 x 0.1 = **0.1**	10 x **0.1** x 10 x 0.1 = **1.0**
$v(S2,odd)$	$= \eta(S2,odd)\beta_{odd}\ \eta(S2,bot)\pi_{bot} =$	10 x **1.0** x 10 x 0.1 = **10.0**	10 x **1.0** x 10 x 0.1 = **10.0**
$v(S2,even)$	$= \eta(S2,even)\beta_{even}\ \eta(S2,bot)\pi_{bot} =$	1 x **1.0** x 10 x 0.1 = **1.0**	1 x **1.0** x 10 x 0.1 = **1.0**
		Σv = 12.1	Σv = 12.1

$\Sigma\Sigma v$ = 133.1

P("x is large")	= (100 + 1)/133.1	= **.759**	(100 + 0.1)/133.1	= **.752**
P("x is small")	= (10 + 0.1)/133.1	= .076	(10 + 1)/133.1	= .083
P("x is odd")	= (10 + 10)/133.1	= .150	(10 + 10)/133.1	= .150
P("x is even")	= (1 + 1)/133.1	= .015	(1 + 1)/133.1	= .015

Figure 7. Executive control of visual attention theory (ECTVA) account of the modulation of crosstalk by task set. The top panel presents ECTVA response to Stimulus 1 (S1), the middle panel presents ECTVA response to S2 when the task set is the same for S1 and S2, and the bottom panel presents ECTVA response to S2 when the task set is different for S1 and S2. Note that the processing rates, v, are determined by two η values. The first one represents the similarity between the stimulus and the to-be-reported category in the response set (determined by β), and the other represents the similarity between the stimulus position and the position that is given priority (determined by π) in the stimulus set. bot = bottom.

effects at long and short SOAs rather than single- and dual-task RT.

ECTVA on concurrence costs. ECTVA has two explanations for concurrence cost. One is in terms of set-switching time. Even the same-task-set condition requires a resetting of the π parameter to refocus attention on S1. The different-task-set condition requires a change of several βs as well. By contrast, no parameters need to be changed in single-task conditions. All that is needed for the next trial are the π and β values from the last trial. The parameter values may need to be "refreshed" occasionally, but not nearly as often as in dual-task conditions.

The second account of concurrence cost involves the old idea of *response conflict* (Berlyne, 1957; Herman & Kantowitz, 1970). There are more potential responses in dual-task conditions than in single-task conditions, and we assume that subjects try to prepare all potential responses before each trial. We assume that the prepared responses compete against each other. The more responses, the stronger the competition. Following Berlyne (1957) and Herman and Kantowitz (1970), we assume that response competition takes time to resolve, and the stronger the competition, the greater the amount of time required for resolution. Thus, RT1 should be longer in dual-task conditions than in single-task control conditions because R1 suffers more competition from other responses in the dual-task context.

Response competition also provides an account of a puzzling but persistent finding in Logan and Schulkind's (2000) data, that RT2 was faster than RT1 at long SOAs (also see the present experiments). We assume that subjects stop preparing the alternatives for R1 once R1 is executed and start preparing only the alternatives for R2. Thus, there would be less response competition when R2 was executed than when R1 was executed. At long SOAs, this weaker competition would allow RT2 to become faster than RT1.

ECTVA accounts for response competition in terms of properties that are already part of EBRW. In EBRW, the winning response has to accumulate K more counts than the next highest alternative. The more responses, the greater the likelihood that an inappropriate response will accumulate a large number of counts and force the correct counter to accumulate more counts to exceed the difference criterion K. We assumed that two random-walk counters were used in single-task conditions but that four were used during Task 1 in the dual-task condition, two for each stimulus (S1 and S2). Thus, R1 had to beat only one incorrect alternative in single-task conditions, but it had to beat the largest of three alternatives in dual-task conditions. The largest of three is likely to be larger than the value in a single counter, so RT1 would be longer in dual-task conditions than in single-task controls. We assumed that ECTVA "jettisoned" the response alternatives for Task 1 when R1 was executed, so that only two random-walk counters would be considered during Task 2. Then the correct counter had to exceed only one incorrect counter, and this sped RT2, relative to RT1, and resulted in RT2 being faster than RT1 at the longest SOAs (see Logan & Schulkind, 2000).

Crosstalk in single- and dual-task conditions. ECTVA predicts stronger crosstalk in dual-task conditions than in single-task conditions, provided that the task set is the same. Crosstalk is reduced in single-task conditions for the same reason it is reduced in different-task-set dual-task conditions: ECTVA can set βs separately for S1 and S2, and it sets βs for the irrelevant stimulus low in single-task conditions. This reduces the processing rates for categorizations of the irrelevant stimulus, and that reduces their impact on choice probabilities for the relevant stimulus (see Equation 17).

The Experiments

We performed three experiments to test the ECTVA predictions and to obtain data sets to model with ECTVA. The first two experiments addressed crosstalk and concurrence cost. In Experiment 1 we compared single- and dual-task conditions within subjects. In Experiment 2 we compared them between subjects and tested an assumption, implicit in Equation 17, that stimulus repetition is not necessary to produce crosstalk. In Experiment 3 we addressed the interaction between set switching and crosstalk, to see whether ECTVA could account for the modulation of crosstalk by task set. To keep the presentation brief, details of the methods and analyses with inferential statistics are presented in Appendices B, D, and E for Experiments 1, 2, and 3, respectively. The details of ECTVA simulations of the experiments appear in Appendixes C, F, and G, respectively.

Experiment 1: Concurrence Cost and Crosstalk

In Experiment 1 we examined concurrence cost and crosstalk. Subjects saw two digits on each trial and made magnitude judgments about them. In the dual-task condition they had to decide whether each digit was greater than 5 or less than 5. Thus, their task set remained the same from Task 1 to Task 2. In the single-task condition they had to decide whether the first digit was greater or less than 5 and ignore the second digit. If there are concurrence costs in the PRP procedure, RT1 should be slower in dual-task conditions than in single-task conditions.

In Experiment 1 we also examined crosstalk from bottleneck or postbottleneck processes in Task 2 to Task 1. The digits on each trial could be congruent (i.e., both greater than 5 or both less than 5) or incongruent (i.e., one greater than 5 and one less than 5). This congruency effect is most likely a response repetition effect (Pashler & Baylis, 1991), which is supposed to affect bottleneck or postbottleneck processes (Pashler & Johnston, 1989).

There were four SOAs: 0, 100, 300, and 900 ms. The details of the procedure can be found in Appendix B.

Results. The mean RTs for single- and dual-task conditions are plotted as a function of SOA in Figure 8. The accuracy data and inferential statistics are presented in Appendix B. RT2 decreased substantially as SOA increased, while RT1 increased slightly. There was a strong concurrence cost: Subjects took 179 ms longer to respond to S1 in dual-task conditions. There was also a crosstalk effect: Subjects were faster when S1 and S2 were both large or both small than when one was large and the other was small. This crosstalk effect averaged 29, 90, and -3 ms for RT1 dual task, RT2 dual task, and RT1 single task, respectively. Finally, RT2 was 167 ms faster than RT1 at the longest (900-ms) SOA, which challenges the idea that RT1 is equivalent to single-task controls.

Discussion. This experiment replicated the standard PRP effects in RT1 and RT2. On average, RT2 decreased by 296 ms from SOA = 0 to SOA = 300 ms, which is very close to the 300-ms

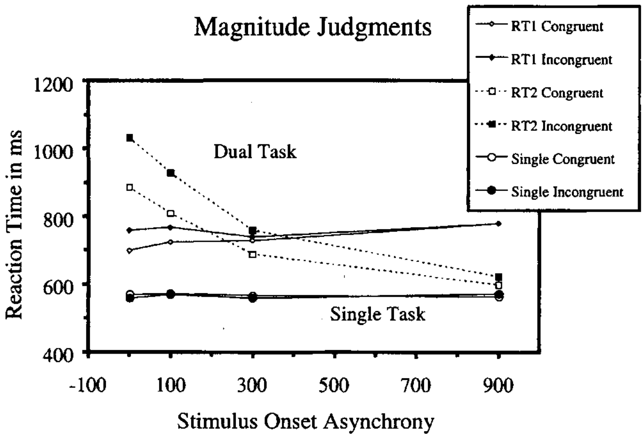

Figure 8. Mean reaction time (RT) in single- and dual-task conditions as a function of stimulus onset asynchrony for magnitude judgments in Experiment 1. RT1 = RT to Stimulus 1 (S1) in dual-task conditions; RT2 = RT to S2 in dual-task conditions; Single = RT to S1 in single-task conditions; Congruent = first and second stimuli in the same response category; Incongruent = first and second stimuli in different response categories.

value one would expect if the slope were −1. We also found a strong concurrence cost and strong crosstalk effects in dual-task conditions for both RT1 and RT2. Subjects responded faster if S1 and S2 were both greater than 5 or both less than 5 than if one was greater than 5 and the other was smaller. The congruency effect on RT1 suggests that response selection for S2 began before response selection for S1 was complete (Logan & Delheimer, in press; Logan & Schulkind, 2000; Townsend & Ashby, 1983). This congruency effect is mostly a response repetition effect, because stimulus repetitions were quite rare, occurring on 12.5% of the trials. We analyzed stimulus repetitions separately from response repetitions and found a congruency effect in both cases, although it was somewhat stronger for stimulus repetitions (see Appendix B).

We found essentially no crosstalk in single-task conditions, in contrast with the strong crosstalk we found in RT1 and RT2. ECTVA predicted this modulation in crosstalk by single- versus dual-task conditions.

ECTVA analysis. We simulated Experiment 1 with ECTVA. The details of the simulation, including accuracies, which were high, are presented in Appendix C. The simulated RTs are presented in Figure 9. ECTVA produced the concurrence costs seen in the data from our subjects. These costs are due in part to set switching; π had to be set high to select S1 before dual-task Task 1 could begin, whereas no such resetting of π was required in single-task conditions. The costs were due in part to response competition. Four counters had to be compared with the random-walk threshold to choose R1 in dual-task conditions, whereas only two counters had to be compared in single-task conditions. Differential response competition also made RT2 faster than RT1 at the longest SOA. Four counters had to be compared for R1, but only two had to be compared for R2.

ECTVA also produced the crosstalk observed in dual-task conditions. The predicted crosstalk effect was larger for RT2 than for RT1, as in our subjects' data, and the RT1 effect diminished as SOA increased, as in our subjects' data. RT2 crosstalk also decreased over SOA (from 143 ms to 88 ms) but not as much as in our subjects' data (from 146 ms to 24 ms). It is likely that the reduction in the RT2 crosstalk we observed at the 900-ms SOA is due to some process we have not modeled. Subjects may inhibit counters more completely when SOA is long. The inhibition process may be repeated, reducing the values in the counters further, or it may take time to have its effect, so that the values decrease continuously over time. Alternatively, subjects may have time to turn down β for Task 1 when SOA is long, to reduce the impact of S1 on selection of R2. We leave these details for future investigations. At present, we are more interested in capturing the qualitative pattern with a simple version of ECTVA than in accounting for all the systematic variance in the data (see Hintzman, 1991). The fits in Figure 9 were obtained by turning parameters off and on (π and β were 1.0 or 0.1, and η was 10 or 1, regardless of SOA).

The crosstalk in RT1 occurred because we kept β high for Task 2 classifications throughout Task 1. The crosstalk in RT2 derives from two sources: β for Task 1 is high throughout Task 2, and the counters retain the pattern they contained when R1 was executed, although its amplitude is reduced by 90%. The residual values in the counters favor RT2 when S1 and S2 are compatible and hinder RT2 when S1 and S2 are incompatible. ECTVA also produced the reduction in crosstalk in single-task conditions, relative to RT1, that it predicted a priori and that was observed in our data. This occurred because β for S2 categorizations was low in single-task conditions and high in dual-task conditions.

Experiment 2: Concurrence Cost, Crosstalk, and Overlap of Task Set

In the second experiment subjects saw a centrally presented word with two colored bars, one above and one below it. The

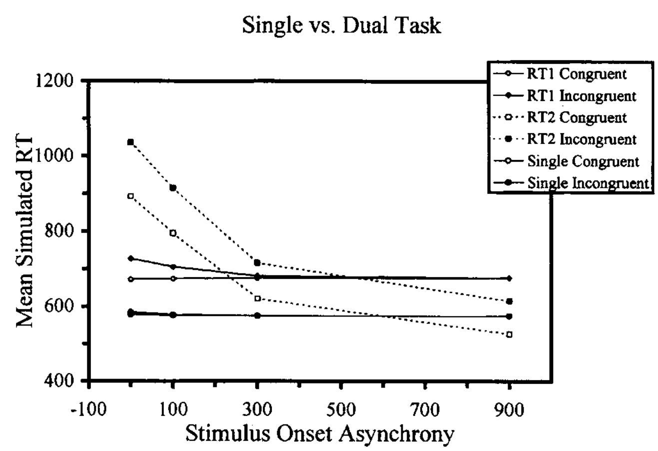

Figure 9. Executive control of visual attention theory simulation of mean reaction time (RT) from Experiment 1 in single- and dual-task conditions as a function of stimulus onset asynchrony in Experiment 1. RT1 = RT to Stimulus 1 (S1) in dual-task conditions; RT2 = RT to S2 in dual-task conditions; Single = RT to S1 in single-task conditions; Congruent = S1 and S2 in the same response category; Incongruent = S1 and S2 in different response categories.

words were *RED, GREEN,* and *BLUE,* and the colors were red, green, and blue. Colors and words were combined randomly, so one third of the trials involved congruent combinations (e.g., RED surrounded by red color bars), and two thirds involved incongruent combinations (e.g., RED surrounded by blue color bars). Subjects performed one or two tasks on these stimuli. Dual-task subjects responded to both the word and the color bar on each trial. Single-task subjects responded only to the word or only to the color. Our main goal was to see whether crosstalk and concurrence costs would appear with this procedure.

Experiment 2 differed from Experiment 1 in that the task set was not identical for Task 1 and Task 2. Task 1 addressed colors, and Task 2 addressed words (or vice versa). As in the previous experiment, the responses were different; subjects responded to Task 1 with their right hands and to Task 2 with their left hands. The task-relevant categorizations overlapped, however. Hommel's (1998) experiments suggest this is sufficient to produce crosstalk between responses, but responses in his experiments were typically made to different attributes of the same stimulus. Our experiment extends Hommel's results to separate stimuli, which is more typical of the PRP procedure.

In this experiment we tested an ECTVA prediction, implicit in Equation 17, that stimulus repetition is not necessary to produce crosstalk between tasks. The crosstalk described in Equation 17 occurs postcategorically because categorizations rather than stimuli are confused. It should not matter whether the categorizations came from the same kind of stimulus or from different kinds of stimuli. In Experiment 2 we tested this prediction by using different stimuli for Task 1 and Task 2 (words vs. color bars). If stimulus repetition is necessary to produce crosstalk, we should see no crosstalk here.

We expected crosstalk between the color and word task because Experiment 2 is a conceptual replication of the classic Stroop (1935) effect. In hundreds of experiments, subjects have been found to be slower to name the color of the stimulus when a concurrent word is the name of another color (for a review, see MacLeod, 1991). The original Stroop effect was observed with integral colors and words (e.g., RED written in green ink), but many researchers have found strong Stroop effects when the color and word are presented separately, as in the present experiment (e.g., RED surrounded by green color bars; e.g., Glaser & Glaser, 1982; Kahneman & Chajczyck, 1983). Our single-task conditions replicate this procedure, so they should replicate the standard Stroop effect. The main questions were whether there would be crosstalk between the colors and the words in dual-task conditions and whether crosstalk would be stronger in dual-task conditions than in single-task conditions, as ECTVA predicts.

There were four SOAs: 0, 100, 300, and 900 ms. Single- versus dual-task conditions varied between subjects. In the single-task conditions, some subjects responded to S1 while others responded to S2. The remaining details of the method appear in Appendix D.

Results. Mean RTs for responses to the color in single- and dual-task conditions are plotted as a function of SOA in Figure 10A. Mean RTs for responses to the word are plotted similarly in Figure 10B. Accuracy and inferential statistics are presented in Appendix D. The mean RTs from the dual-task conditions replicate the basic PRP effects: RT1 was relatively unaffected by SOA, while RT2 was strongly affected. In addition, we observed three

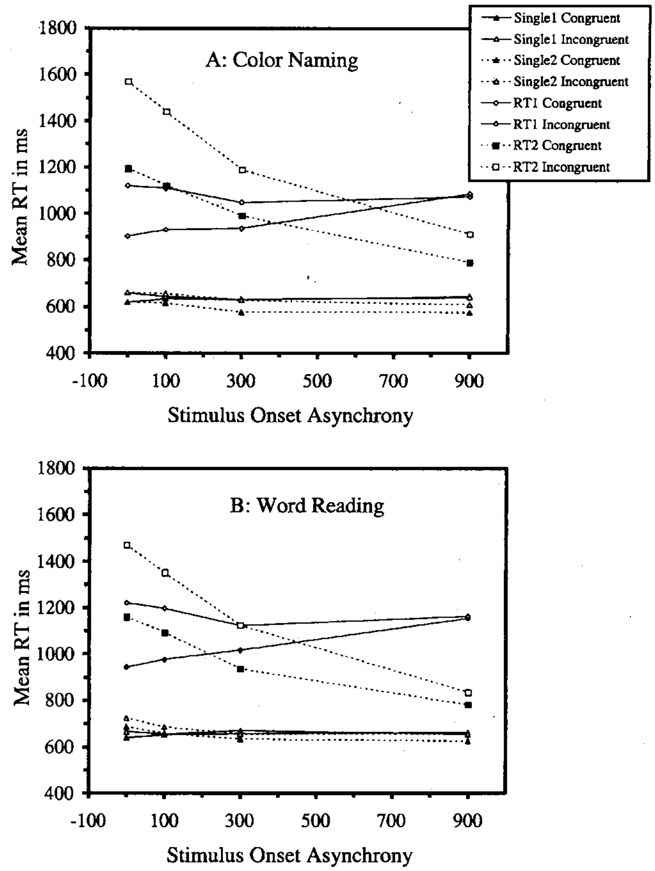

Figure 10. Mean reaction times (RTs) for color naming responses (Panel A) and word reading responses (Panel B) in single- and dual-task conditions in Experiment 2. Single1 = RT to Stimulus 1 (S1) in single-task conditions; Single2 = RT to S2 in single-task conditions; RT1 = RT to S1 in dual-task conditions; RT2 = RT to S2 in dual-task conditions; Congruent = S1 and S2 in the same response category; Incongruent = S1 and S2 in different response categories.

theoretically relevant effects: First, there were substantial concurrence costs. On average, RT1 was 415 ms slower in dual-task conditions than in single-task conditions, and RT2 was 481 ms slower. Second, there was substantial crosstalk between tasks. In dual-task conditions the congruency effect averaged 139 ms for RT1 and 228 ms for RT2. The crosstalk effects were much larger in dual-task conditions than in single-task conditions. The single-task averages were 10 ms for RT1 and 36 ms for RT2. Third, we found that RT2 was 289 ms faster than RT1, on average, at the longest SOA.

Discussion. This experiment revealed strong concurrence costs and crosstalk effects. Subjects were faster in single-task conditions than in dual-task conditions. Subjects were also faster if the color and word were congruent than if they were incongruent. This effect was an order of magnitude stronger in dual-task conditions than in single-task conditions. It is significant that we observed strong crosstalk on RT1 in the dual-task conditions. Given the evidence from the literature that response selection is the primary locus of the Stroop effect (Fagot & Pashler, 1992), the crosstalk effects on RT1 suggest that Task 2 response selection began before Task 1 response selection finished.

It is significant that we found crosstalk when the stimuli for the two tasks were different. This supports the ECTVA prediction that stimulus repetition is not necessary to produce crosstalk (see Equation 17). This experiment, together with Hommel's (1998) experiments, suggests that overlap of stimulus classifications or response descriptions is sufficient to produce crosstalk between tasks.

ECTVA analysis. The ECTVA simulation of Experiment 2 is described in detail in Appendix E. Appendix E also reports the accuracies, which were high. The simulated RT data appear in Figure 11. In its present form, ECTVA does not distinguish between reporting the word and reporting the color, so we did not run separate simulations for each task.

As Figure 11 shows, ECTVA captured the major RT results. Single-task RT1 and RT2 were fast and unaffected by SOA and showed small crosstalk effects. Again, ECTVA captured concurrence costs. Single-task RT1 and RT2 were both faster than dual-task RT1. Dual-task RT1 showed a crosstalk effect that was larger than the one in the single-task RT1 and RT2 data. Finally, dual-task RT2 showed a crosstalk effect that was even stronger than the one observed in dual-task RT1, as it was in the data. The simulated interaction between congruency and SOA was weaker than the observed interactions. The stronger interaction in the observed data may be due to processes we did not model (see, e.g., Meyer & Kieras, 1997b).

The mechanisms that produced these effects were the same as in Experiment 1. Concurrence cost was due to set-switching costs (setting π for S1) and response competition (six counters in dual-task conditions; three in single-task conditions). Crosstalk in dual-task conditions occurred because the βs were high for Task 2 during Task 1 and the post-R1 inhibition process left the pattern in

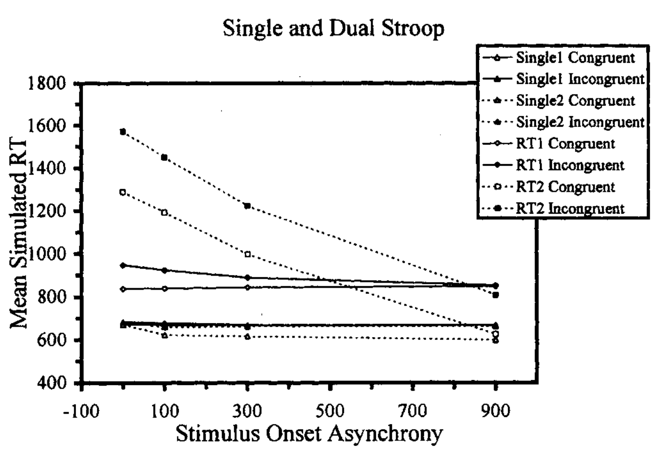

Figure 11. Executive control of visual attention theory simulation of mean reaction time (RT) from Experiment 2 in single- and dual-task conditions as a function of stimulus onset asynchrony in Experiment 1. Single1 = RT to Stimulus 1 (S1) in single-task conditions; Single2 = RT to S2 in single-task conditions; RT1 = RT to S1 in dual-task conditions; RT2 = RT to S2 in dual-task conditions; Congruent = S1 and S2 in the same response category; Incongruent = S1 and S2 in different response categories.

the counters that produced R1, reduced to 10% of its amplitude. The crosstalk is postcategorical in that there was no overlap in stimulus representations. Crosstalk was reduced in single-task conditions because β was low for all categorizations of the to-be-ignored stimulus.

Experiment 3: Set-Switching Costs and Crosstalk

The third experiment addressed the effects of switching sets from Task 1 to Task 2 within a trial and from Task 2 to Task 1 from one trial to the next. S1 and S2 were pictures or words. Half of the pictures depicted animals, and half depicted nonanimals. Half of the words named animals, and half named nonanimals. There were two different task sets: *form* judgments and *animacy* judgments. In the form judgment task, subjects decided whether the stimulus was a picture or a word; in the animacy judgment task, they decided whether the stimulus represented an animal. Subjects performed the same task on S1 and S2 for two sessions and different tasks on S1 and S2 for another two sessions. We used all four combinations of tasks and stimuli, and each subject was tested on each combination in a different session. One same-task session required animacy judgments on S1 and S2. The other same-task session required form judgments on S1 and S2. One different-task session required animacy judgments on S1 and form judgments on S2, while the other different-task session required form judgments on S1 and animacy judgments on S2. If there are set-switching costs in the PRP procedure, then performance should be worse in the different-task conditions than in the same-task conditions. The effects could appear in both RT1 and RT2.

In Experiment 3 we also manipulated crosstalk between tasks. In each condition, S1 and S2 were congruent on half of the trials and incongruent on the other half. In the form task, half of the trials involved picture–picture or word–word sequences for S1 and S2, and half involved picture–word or word–picture sequences. In the animacy task, half of the stimuli involved animal–animal or nonanimal–nonanimal sequences, and half involved animal–nonanimal or nonanimal–animal sequences. If there is crosstalk between tasks, RT1 and RT2 should be faster when the stimuli are congruent than when they are incongruent.

There were three SOAs: 0, 400, and 1,000 ms. The details of the method can be found in Appendix F.

Results: Form task. Mean RT1 and RT2 for form judgments are plotted as a function of SOA in Figure 12. Percentage of correct responses and inferential statistics appear in Appendix F. The data replicated the basic PRP effects: RT1 was not affected much by SOA, but RT2 was strongly affected. There were strong set-switching effects for both RT1 and RT2. RT1 was 215 ms slower when the task set changed than when it stayed the same. RT2 was 500 ms slower. However, the set-switching effects on RT2 include a Task 1 difficulty effect: RT1 was 137 ms faster on average in the form task than in the animacy task, so same-task RT2 should be 137 ms faster than different-task RT2 even if there were no set-switching costs. Thus, the true set-switching effect on form judgment RT2 may be estimated more accurately by subtracting the difference in RT1 from the observed set-switching cost, producing a value of 500 − 137 = 363 ms.

There were strong crosstalk effects that interacted with set switching. When the task set was the same, RT1 was 50 ms faster

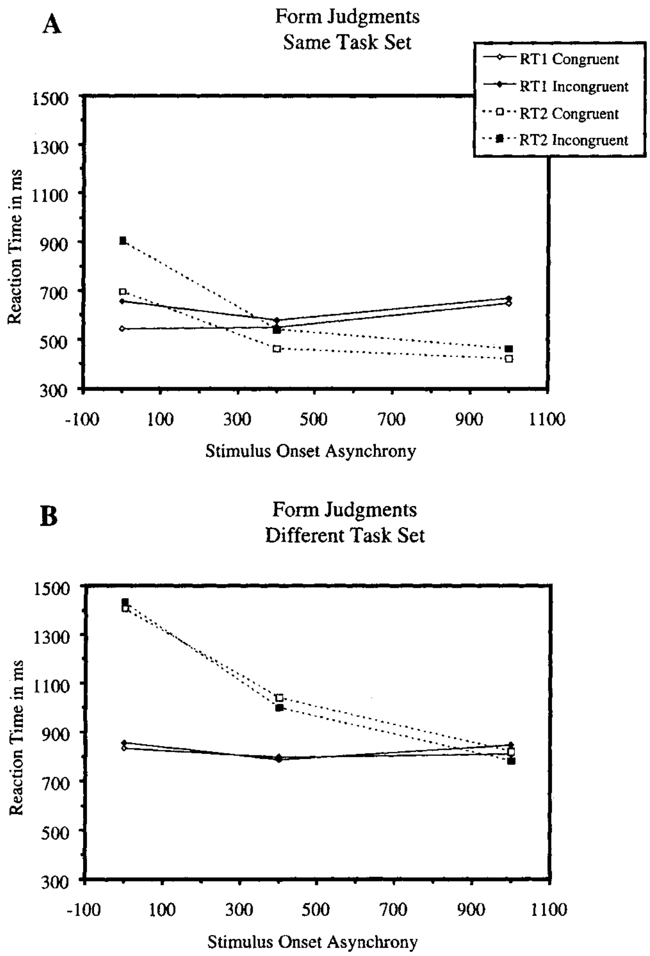

Figure 12. Mean reaction times (RTs) for form judgments in same task set (Panel A) and different task set (Panel B) conditions as a function of stimulus onset asynchrony in Experiment 2. RT1 = RT to Stimulus 1 (S1); RT2 = RT to S2; Congruent = S1 and S2 in the same response category; Incongruent = S1 and S2 in different response categories.

when S1 and S2 were congruent than when they were incongruent. When task set changed from form on S1 to animacy on S2, RT1 was 9 ms slower when S1 and S2 were congruent. The crosstalk effect in the same-task-set condition was stronger when SOA was short than when it was long, averaging 111, 27, and 11 ms for SOAs of 0, 400, and 1,000 ms, respectively.

The same interaction between task set and crosstalk was apparent in the RT2 data. When the task set was the same, the form-congruency effect was 109 ms; when the task set was different, the form-congruency effect reversed slightly (−18 ms). The form-congruency effect in the same-task-set condition decreased as SOA increased, averaging 209, 78, and 41 ms for SOAs of 0, 400, and 1,000 ms, respectively.

Results: Animacy task. Mean RT1 and RT2 for animacy judgments are plotted as a function of SOA in Figure 13. Accuracy data and inferential statistics appear in Appendix F. The animacy data replicate basic PRP effects as well: RT1 was not affected much by SOA, whereas RT2 decreased sharply as SOA increased. As with form judgments, the animacy task produced strong set-switching effects. RT1 was 244 ms slower when the task set changed than when it stayed the same. This set-switching cost was about the same magnitude as the one found with form judgments in Task 1 (215 ms). RT2 was 218 ms slower overall when the task set changed, but that difference includes a 137-ms difference in Task 1 difficulty in favor of the different-task-set condition. A more accurate estimate can be obtained by adding this difference to the observed set-switching difference, yielding 137 + 218 = 355 ms. That value is quite close to the corrected value when Task 2 required form judgments (363 ms; cf. Allport et al., 1994).

The crosstalk effects in the animacy task were smaller, but they followed the same pattern as the effects in the form task. They were modulated by task set in the same manner. When the task set was the same, RT1 was 28 ms faster when S1 and S2 were congruent than when they were incongruent. When the task set was different, the congruency effect disappeared. RT1 was 2 ms slower if S1 and S2 were congruent. The congruency effect was modu-

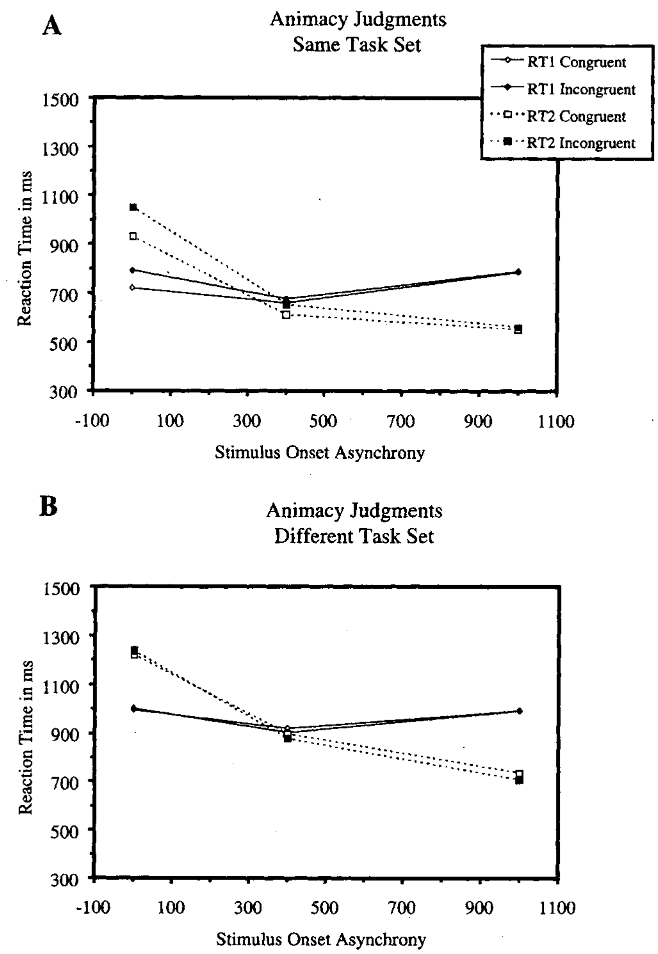

Figure 13. Mean reaction times (RTs) for animacy judgments in same task set (Panel A) and different task set (Panel B) conditions as a function of stimulus onset asynchrony in Experiment 2. RT1 = RT to Stimulus 1 (S1); RT2 = RT to S2; Congruent = S1 and S2 in the same response category; Incongruent = S1 and S2 in different response categories.

lated by SOA in the same-task-set condition, just like the form congruency effect. The animacy congruency effect was 71, 15, and −1 ms for SOAs of 0, 100, and 400 ms, respectively.

The animacy congruency effect in RT2 was stronger, but it too was modulated by task set. When the task set was the same, RT2 was 64 ms faster when S1 and S2 were congruent, whereas when the task set was different RT2 was 11 ms slower when S1 and S2 were congruent. The congruency effect in the same-task-set condition decreased over SOA, averaging 121, 43, and 28 ms for SOAs of 0, 400, and 1,000 ms, respectively.

Discussion. This experiment replicated classic PRP results: RT1 was largely unaffected by SOA, but RT2 was strongly affected. This experiment also showed strong set-switching costs. RT1 and RT2 were both longer when the task set changed from Task 1 to Task 2 than when it stayed the same. This experiment replicated crosstalk from Task 2 to Task 1 in two new tasks: form judgments and animacy judgments. The experiment also showed that crosstalk between tasks depended on the task set being the same for Task 1 and Task 2. No crosstalk was found when the task set changed from Task 1 to Task 2.

It is interesting that the crosstalk effects were stronger in the form judgment task than in the animacy judgment task. Animacy judgments likely required more difficult discriminations. The pictures and words had to activate semantic memory before an animacy judgment was possible, whereas many simple features distinguish pictures from words. It was interesting as well that the set-switching costs were about the same for form judgments and animacy judgments, despite the difference in propensity to produce crosstalk (cf. Allport et al., 1994). It suggests that the mechanisms that produce crosstalk may be different from those responsible for set-switching costs, as we assumed.

Comparison with Logan and Schulkind's (2000) Experiment 2. Figure 14 contains the data from Logan and Schulkind's (2000) PRP experiment on set switching that used magnitude and parity judgments. The same effects were found with both judgments, so the data in Figure 14 are collapsed across judgment type. The data show the same effects seen in our present Experiment 3: RT1 and RT2 were both longer in the different-task condition than in the same-task condition, evidencing set-switching costs. There was strong crosstalk in both RT1 and RT2 in the same-task condition, but that crosstalk almost disappeared in the different-task condition. This suggests that the results of the present Experiment 3 generalize to different tasks and different materials.

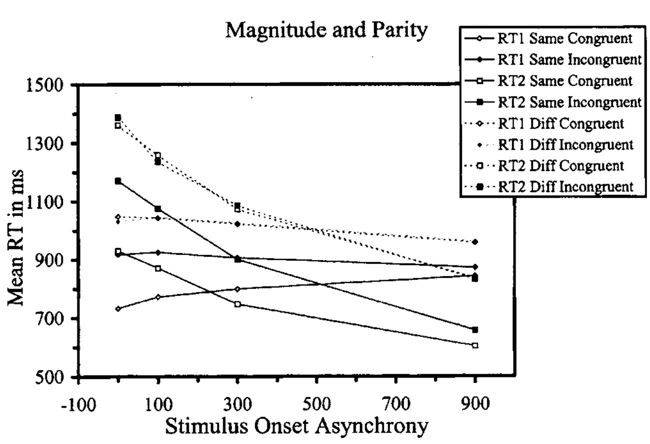

Figure 14. Mean reaction times (RTs) as a function of stimulus onset asynchrony for parity and magnitude judgments when the task set is the same for the first and second stimuli (solid lines) and when the task set is different (broken lines). RT1 = RT to Stimulus 1 (S1); RT2 = RT to S2; Congruent = S1 and S2 in the same response category; Incongruent = S1 and S2 in different (Diff) response categories.

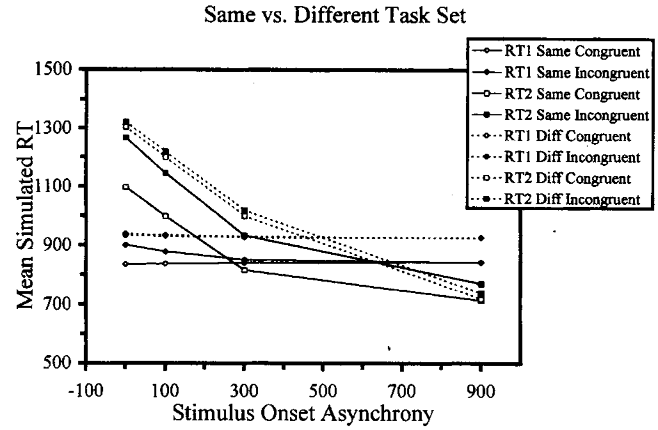

Figure 15. Executive control of visual attention theory simulation of mean reaction times (RTs) from Logan and Schulkind's (2000) Experiment 2 when the task set is the same (solid lines) and when the task set is different (broken lines) as a function of stimulus onset asynchrony. RT1 = RT to Stimulus 1 (S1); RT2 = RT to S2; Congruent = S1 and S2 in the same response category; Incongruent = S1 and S2 in different (Diff) response categories.

ECTVA analysis. We simulated Logan and Schulkind's (2000) Experiment 2. The details of the simulation and the simulated accuracy data are presented in Appendix G. The simulated RT data are presented in Figure 15. The basic PRP effects obtained for RT1 and RT2, and there was strong crosstalk observed in both RT1 and RT2. The different-task conditions show strong set-switching costs but no crosstalk. RT1 and RT2 were both longer in the different-task condition than in the same-task condition, but the congruency of S1 and S2 categorization had no impact on RT1 or RT2. Thus, ECTVA can capture the major effects in the present Experiment 3 and in Logan and Schulkind's Experiment 2.

The crosstalk in the same-task conditions occurred for the reasons described earlier: RT1 crosstalk is due to high βs for S2 categorizations, and RT2 crosstalk is due to the residual left in the counters after post-R1 inhibition as well as high βs for S1 categorizations. The lack of crosstalk in the different-task-set conditions occurred because the βs were different for S1 and S2 (see Figure 7). When Task 1 was underway, the relevant Task 2 categorizations were attenuated by low βs; when Task 2 was underway, Task 1 categorizations attenuated similarly. Moreover, the different-task-set condition leaves a residual pattern in the counters that is irrelevant to Task 2. It may slow R2, making it take more counts to achieve K more categorizations in favor of the correct alternative, but it does not bias R2 toward the correct response or the other one.

General Discussion

The experiments showed that three effects identified with executive processing occur in the PRP procedure: crosstalk, set-switching costs, and concurrence costs. The simulations showed that ECTVA could account for the main effects of these variables and their interactions. These results have implications for the PRP literature, suggesting ways to integrate the theories as well as to distinguish them. They have implications for the literature on set switching and executive processing, suggesting ways to instantiate the initial theories more concretely by grounding them in a specific theory of subordinate processing. Our theoretical treatment of the results has implications for the relation between perceptual attention and response-oriented attention and for modularity in theorizing about cognition.

ECTVA, Present and Future

ECTVA adds four main ideas to extend single-task TVA to dual-task situations. First, it assumes that task sets are sets of homunculus-controlled parameters in TVA (i.e., c, β, π, and K). This implies that switching sets involves changing TVA control parameters, and that implies that set-switching time is a function of the number of parameters to be changed (Equation 18). Set-switching time accounts for set-switching costs and some concurrence costs. Second, ECTVA assumes that βs can be assigned separately to S1 and S2. The βs are responsible for crosstalk from S2 to S1 and from S1 to S2, and the ability to assign βs separately to S1 and S2 is responsible for the modulation of crosstalk by task set and by single- versus dual-task conditions. Third, ECTVA assumes that subjects solve the dual-task binding problem by making TVA run serially, manipulating π. First, it sets π high for S1 and low for S2 to run Task 1. Then it sets π high for S2 and low for S1 to run Task 2. The serial strategy implies the basic PRP effects: Task 1 runs first, so it is unaffected by SOA. Task 2 runs second, so RT2 depends on SOA; it includes the time that Task 2 has to wait for Task 1 to finish. Fourth, ECTVA assumes that subjects solve the dual-task serial order problem by inhibiting the random-walk counters so that the difference between them is less than the criterion K. This accounts for the ability to avoid perseverating on R1 and select R2, and it accounts for some of the crosstalk from S1 to S2. These ideas add two parameters to the model: one representing the time required to change a TVA parameter and one representing the amount by which the random-walk counters are inhibited. Together with the assumptions that are already part of TVA (and EBRW), these assumptions account for data from the experiments we report.

The version of ECTVA that we developed deals with PRP situations with similar stimuli, similar tasks, and similar responses. More general versions of ECTVA may be developed to deal with a broader range of situations. A more general version may replace the specific version we developed here. An intriguing possibility is that the more general version may incorporate the specific version we developed as a special case or an initial strategy, and subjects may move from one version to another by learning. Subjects may start a new PRP situation with the version of ECTVA we developed here—solving the binding problem by processing S1 and S2 in series and solving the serial order problem by inhibiting all the counters—and learn another version of ECTVA that is tailored to the particulars of the situation in which they find themselves. Some aspects of performance change dramatically with practice in dual-task situations (Logan, 1979; Spelke, Hirst, & Neisser, 1976; but see Van Selst, Ruthruff, & Johnston, 1999). We consider three potential changes in ECTVA.

Different solution to the binding problem. The binding problem occurs when categorizations of S1 and S2 are confusable (Equation 17). Serial processing allows the system to attribute categorizations to the currently prioritized stimulus. Different solutions to the binding problem may be possible if the categorizations of S1 and S2 are not confusable, and those solutions may not require serial responding (see, e.g., Meyer & Kieras, 1997b). Subjects may use the content of the categorization to attribute it to a stimulus. For example, if Task 1 were discriminating high and low tones, and Task 2 were discriminating vowels and consonants, the categorizations themselves could be used to identify the stimulus from which they came. "High" would be more likely to come from the tone than the letter; "vowel" would be more likely to come from the letter than the tone. Subjects may solve the binding problem early in practice by processing S1 and S2 in series but then learn to use categorization content to solve the problem as they gain experience with the task and consequently process S1 and S2 in parallel. The idea that subjects change the way they solve problems over practice has some currency in the literature (e.g., Anderson, 1993; Logan, 1988).

Different solution to the problem of comparing counter values. ECTVA assumes that EBRW can evaluate only one difference criterion at a time. This assumption is central to its predictions about serial responding and its explanation of concurrence costs. We chose this assumption partly because it was simple—finding the largest value in a set is straightforward and easy to implement—and because it was already part of random-walk models that exist in the literature (e.g., Nosofsky & Palmeri, 1997; Ratcliff, 1978, 1988). It may be possible to develop choice rules that look at other differences between the counters, but they are likely to be more complicated than the simple rule implemented in EBRW. The choice rules may be viewed as alternative theories that should be distinguished from each other or as alternative strategies that are related by learning. Subjects may begin with ECTVA and learn a more efficient strategy.

One possibility would be to divide the set of response counters into two—one for Task 1 and one for Task 2—and compare each set separately with its own criterion. This would be easier if Task 1 and Task 2 were very different from each other. Experiment 3 and Equation 17 suggest that similarity of response categories (overlap in βs) is more critical than stimulus similarity. Whether subjects can learn to divide response sets in this manner is a question for future research.

Different solution to the serial order problem. ECTVA prevents perseveration of R1 by inhibiting all of the random-walk counters and thereby inhibiting all possible responses. Models of serial order typically prevent perseveration by inhibiting only the response that was just executed, leaving the others active and available to be selected in the next cycle (e.g., Bryden, 1967; Dell et al., 1997; Estes, 1972; MacKay, 1987; Rumelhart & Norman, 1982). The difference may reflect level of skill: ECTVA applies to novice PRP performance, whereas models of serial order usually apply to highly skilled behaviors, such as speaking and typing. It may be possible that people impose serial order by inhibiting all responses early in practice and then learn to inhibit only the just-executed response as they gain experience with the task. Alternatively, ECTVA may work just as well if only the just-executed response is inhibited. Preliminary simulations suggest that the pattern of effects does not change much when this assumption is changed.

ECTVA, RSB, and SRD

In the introduction of this article, we suggested that ECTVA could be viewed as an elaboration of RSB and SRD or as a competitive theory. At this point it may be more appropriate to view ECTVA as an elaboration. ECTVA covers a small part of the PRP literature in which S1 and S2 are both visual. The theory would have to be extended considerably to deal with stimuli with significant spatial or temporal structure. ECTVA says nothing about early perceptual processes and late response-execution processes (see Figure 2), and those processes play important roles in PRP phenomena.

Viewed as a competitor, ECTVA seems to challenge RSB more than SRD. ECTVA's assumption that stimulus selection and response selection are cascaded (Ashby, 1982; McClelland, 1979) contrasts with RSB's assumption that they are discrete. The assumption of discrete stages is essential to the locus of slack logic that provides the theoretical foundation for RSB (Schweickert, 1978; Schweickert & Townsend, 1989; Townsend & Schweickert, 1989). The evidence for crosstalk from S2 to S1 challenges RSB's assumption that response selection is serial and discrete. It suggests that Task 2 response selection began before Task 1 response selection was complete (also see Logan & Delheimer, in press; Logan & Schulkind, 2000). If response selection were serial and discrete, Task 2 response selection could not begin before Task 1 response selection finished (Townsend & Ashby, 1983). ECTVA illustrates one interpretation of parallel response selection: Evidence for all possible responses accumulates in the counters before the random walk terminates. These challenges may stimulate RSB theorists to develop more detailed theories of response selection, and that would be good for the field. ECTVA may turn out to be a special case rather than a competitor.

The inhibition of the random-walk counters provides the current version of ECTVA with a way to salvage RSB's assumption that response selection is serial and discrete.[6] Crosstalk from S2 to S1 implies that information about S2 was available before R1 was selected, but it does not imply that that information was used to select R2. If all of the S2 information that builds up in the random-walk counters is lost when the counters are inhibited so none remains to influence R2 selection, R2 selection can be said to begin after R1 selection. This would preserve the discrete-stage assumption. If inhibition were almost complete, R2 selection may be approximately discrete, not beginning in earnest until R1 selection was over.

Inhibition of the random-walk counters need not always preserve the discrete-stage assumption. The amount of inhibition can vary from 0 to 100%, and the range of inhibition values that preserves discreteness is narrower than the range that prevents response perseveration. Explorations with the model show that the serial order problem can be solved by inhibiting the counters by as little as 30% (compared to 90% in our simulations). That amount of inhibition (30%) produces a large amount of crosstalk, which suggests a serious violation of the discreteness assumption. Future research will be required to determine whether the amount of inhibition subjects employ is enough to preserve RSB's discrete-stage assumption.

Set Switching

Research on set switching is still in its infancy, despite its relatively long history in experimental psychology (dating to Jersild, 1927). The current theories are not very detailed and not very quantitative. They are more like hypotheses than theories. ECTVA's account of set switching is tailored to the PRP situation, but it could be extended easily to more typical set-switching situations (e.g., Allport et al., 1994; Allport & Wylie, 2000; DeJong, 2000; Jersild, 1927; Meiran, 1996; Rogers & Monsell, 1995). That is an important direction for future research.

Our interpretation of set-switching costs as reflecting the time required to transmit a set of parameters from working memory to TVA contrasts with that of Allport et al. (1994; also see Allport & Wylie, 2000). Allport and his colleagues claim that set-switching costs are due to aftereffects of previous task sets (task set inertia) rather than the time required to instantiate the set. Their view could be accommodated in ECTVA by assuming memory for previous parameter settings. There are at least three possibilities: First, interference could occur in TVA. Parameters from old task sets may remain in TVA and alter the values of new parameters that are transmitted to TVA. The current parameter values may be a weighted average of the current input values and decaying values from the previous task set. Second, interference may occur in working memory. ECTVA assumes that task sets are represented in working memory at the parameter level and the task level. Interference in both kinds of representation could affect the instantiation of the current task set. Finally, interference could occur in long-term memory. Task sets are also represented in long-term memory, and some of the set-switching costs may reflect interference in retrieval from long-term memory rather than working memory or TVA. It remains to be seen whether any of these proposals has merit.

Our assumption that the TVA parameters for Task 1 are transmitted from working memory to TVA after S1 appears is similar to Rogers and Monsell's (1995) view. They argued that some aspects of set switching cannot begin until the relevant stimulus appears (also see Ward, 1982). Our assumption that Task 2 parameters are transmitted as soon as R1 is executed would appear to contradict this view. However, most PRP experiments use SOAs short enough that S2 is presented before R1 occurs, so the set switch occurs well after S2 is presented. Set switching may begin before S2 is presented at the longest SOAs. That occurred at the 900-ms SOA in our simulations. At that SOA, some of the set-switching costs were absorbed into the waiting time between R1 and S2.

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[6] We are grateful to Hal Pashler for pointing this out and discussing its implications.

Our ideas about transmission time suggest a new interpretation of DeJong's (2000) claim that people do not prepare optimally for a new task. DeJong analyzed RT distributions in conditions that required set switching and showed that they were a mixture of two distributions, one in which subjects are fully prepared and one in which subjects are not at all prepared. Our assumption that set switching (parameter transmission) takes time suggests that it may be very difficult to prepare optimally for a new task. Subjects may try to transmit all of the parameters before the relevant stimulus occurs, but it is unlikely that all of the parameters will arrive in TVA at the same time. They may learn, over practice, to trigger transmission based on a more optimal signal event in TVA (e.g., the onset of the warning signal rather than the onset of S1), but they may never get the parameters to arrive simultaneously.

We assumed parallel, unlimited-capacity transmission so that the transmission time of the last parameter to be changed was the maximum of the transmission times for all N parameters, and the maximum transmission time increases with N (see Equation 18). Our assumption of parallel, unlimited-capacity transmission also predicts that the time required to transmit the first parameter decreases as N increases. This follows because the transmission time for the first parameter is the minimum of the transmission times for all N parameters, and the expected value of the minimum of N independent, unlimited-capacity transmission times decreases as N increases (Logan, 1988). If the transmission times are distributed exponentially, then mean transmission time for the first parameter to be transmitted is

$$E(T_{Min}) = \frac{1}{Nv} = \frac{1}{N}\frac{1}{v}. \tag{19}$$

Because the maximum increases with N (Equation 18) and the minimum decreases with N (Equation 19), the parameters will not arrive at TVA at the same time but rather they will arrive over a period of time whose duration increases with N. The duration of this period is given by the difference between Equation 18 and Equation 19 and has the same form as Equation 18:

$$E(T_{Max}) - E(T_{Min}) = \frac{1}{v}\sum_{i=1}^{N}\frac{1}{i} - \frac{1}{v}\frac{1}{N} = \frac{1}{v}\sum_{i=1}^{N-1}\frac{1}{i}.$$

This fact about unlimited-capacity, parallel transmission imposes constraints on the executive's attempts to time parameter transmission so that all parameters are in place at the time the relevant stimulus occurs. If N is large, the first parameters to be transmitted may start to decay before the last few are transmitted, and that may present other problems for the executive to solve. Thus, preparation for a complex task set may never be optimal (cf. DeJong, 2000).

Theories of Executive Processing

ECTVA has several implications for theories of executive processing. The first, discussed earlier, is the need for grounding a theory of executive processing in a computational theory of subordinate processing. The second concerns the nature of task sets and how the executive puts them in place. ECTVA conceives of a task set as a set of parameter values sufficient to make TVA perform goal-relevant categorizations. ECTVA instantiates the task set by transmitting parameters to TVA. The task set is in place when all of the parameters have been transmitted. More generally, ECTVA conceives of task set in terms of *parameter control.* An alternative perspective, drawn from the mind-as-digital-computer analogy, is that a task set is a set of procedures (e.g., processing stages) that are retrieved from memory and put into place much like a program is copied from a disk into a computer's memory before it is executed. Logan (1980b) proposed an idea like this but rejected it in favor of another alternative. Norman and Shallice (1986) seem to fit this analogy when they talk about task sets activating schemas. In our view, parameter control is the more plausible alternative. It seems more likely that one brain area controls another by modulating activity in the other area than by copying something like a program into that other area (Duncan, 1996). Of course, plausibility is a weak criterion. It is limited primarily by one's imagination.

A third, more popular alternative is the idea that task sets involve sets of stimulus–response mapping rules or elementary *productions* in a *production system* (DeJong, 1995; Fagot & Pashler, 1992; Logan, 1980b, 1985; McCann & Johnston, 1992; Meyer & Kieras, 1997a, 1997b). Instantiating a task set means preparing a set of rules to respond to the stimulus. Changing task set means changing the set of rules. ECTVA incorporates this idea in terms of task-level representations in working memory. Those representations can be viewed as sets of rules. However, ECTVA suggests that preparing and changing sets of rules is not sufficient to instantiate or change a task set. The parameters that control the subordinate must be derived from the rule and passed on to the subordinate process. If ECTVA does not change the parameters in TVA, the task set will not change.[7]

Modulation of Crosstalk by Task Set

Experiment 3 demonstrated that crosstalk between S2 and S1 was modulated by task set. Crosstalk occurred if the task set was the same for S1 and S2 but not if the task set was different. Logan and Schulkind (2000) found the same effects with magnitude and parity judgments (see Figure 15). These effects are similar to several effects in the literature that led researchers to propose the idea that some processes were *conditionally automatic* (Bargh, 1992; DeJong, Liang, & Lauber, 1994; Logan, 1988). In the modal view, some processes are automatic in the sense that they are activated regardless of the subject's beliefs and intentions (see Kahneman & Treisman, 1984; Logan, 1988). Our data and data before them suggest that some processes may become active automatically only if they are consistent with the current task set. Their automaticity is conditional on the task set. Smith (1979; Smith, Theodor, & Franklin, 1983) found that semantic priming occurred only if subjects treated the prime as a word. If they treated it as a letter string, by searching for a particular letter in the

[7] Once TVA parameters have been derived from the task-level representation, transmitting them to TVA may be obligatory. That is an interesting question for future research. Our point is that ECTVA adds two critical steps to set switching that must go on after rules have been switched: TVA parameters must be derived from the rules, and they must be transmitted to TVA.

word, there was no semantic priming (also see Chiappe, Smith, & Besner, 1996; Henik, Friedrich, & Kellogg, 1983; McKoon & Ratcliff, 1995; Stolz & Besner, 1996). Besner, Stolz, and Boutilier (1997) showed that the Stroop effect could be eliminated (almost) by coloring only one of the letters of the word (also see Bauer & Besner, 1997).

The ECTVA analyses of crosstalk and the modulation of crosstalk by task set provide some insight into these findings. We interpret priming and Stroop effects as kinds of crosstalk (Logan, 1980a). If the categorizations for one task are relevant to (i.e., congruent with or incongruent with) the categorizations for another task, crosstalk will be observed, following Equation 17 and the ECTVA analysis in Figure 6. The main difference between the PRP situation and Stroop and priming tasks lies in the SOAs used or, alternatively, in terms of the interval between R1 and S2 (*response-to-stimulus interval* [RSI]). SOAs are typically shorter in the PRP procedure, with most of the action happening in the 0–500-ms range, whereas SOAs in typical priming tasks range from 250 to 2,000 ms. The RSIs in the PRP procedure are generally negative—S2 often occurs before R1—whereas the RSIs in priming tasks are typically positive and on the order of 1,000 or 2,000 ms. In our view, these differences are not very important with respect to the modulation of crosstalk by task set. The differences determine the magnitudes of crosstalk effects (Logan, 1980a), but the presence or absence of crosstalk effects depends on the similarity of task set, and that transcends RSI and SOA.

As with set switching, the modulation of crosstalk by task set in Stroop and priming paradigms has not been accounted for very well theoretically. Researchers believe that task set is important, but until ECTVA there was no theoretical account of the modulation of crosstalk by task set. As with set switching, it should be relatively straightforward to extend ECTVA to deal with the modulation of Stroop and priming effects by task set (cf. Logan, 1980a). That remains an important topic for future research.

Modularity in Theorizing

This article began with two challenges: generalize special-purpose theories to cover new phenomena and specify the executive processes that control the special-purpose theories. ECTVA is one specific response to these challenges. ECTVA shows that the basic machinery of TVA can be generalized from single-task studies of focused and divided attention to studies of dual tasks and the PRP in particular. ECTVA runs TVA twice, once on each stimulus. To control TVA's behavior, we had to specify the executive processes involved in changing set.

ECTVA is a modular theory. It is an amalgamation of different components, and some components are more crucial than others. TVA and EBRW are essential; we are less committed to the other parts of the theory. For example, we said little about the CODE part of TVA although CODE makes some very specific assumptions that may prove to be false in future research (see Compton & Logan, 1993, 1999; Van Oeffelen & Vos, 1982, 1983). It should be possible to replace CODE with another theory of perceptual organization. The main requirement, from the perspective of ECTVA, is that the theory of perceptual grouping should provide a number between 0 and 1 that reflects the proportion of the features of an object that can be sampled given a particular perceptual organization.

Similarly, our assumption that parameter transmission is parallel and unlimited in capacity is not essential to the theory. The main requirement for a theory of set switching is that the time required to transmit the set of parameters increases with the number of parameters in the set. A theory of serial transmission would predict a linear increase. Nothing in our data or our theorizing discriminates serial from parallel parameter transmission.

Modular theorizing implies that parts can be replaced. It also implies that parts can be decomposed or unpacked, as molecules can be broken down into atoms. It may prove worthwhile to unpack some of ECTVA's parameters. Nosofsky (1984, 1986, 1988) and Nosofsky and Palmeri (1997) decomposed ECTVA's η parameter into a representation of similarity as distance in multidimensional similarity space. This decomposition proved to be very powerful in accounting for categorization judgments and for the relations between categorization and recognition and between categorization and identification (also see Ashby & Maddox, 1993). A similar sort of decomposition could be incorporated into ECTVA to increase its power and scope (see Logan, 2001).

A deeper issue underlying modularity is the falsifiability of ECTVA. If none of the theories that comprise it is critical, how can the theory as a whole be falsified? This is an important question, but it is one that we prefer to put off until some time in the future when we have discovered what ECTVA can do and what configurations of component theories seem necessary to account for a broad range of phenomena. It would be easy to falsify some of the specific assumptions that go into ECTVA (e.g., that the distribution of finishing times is exponential), but that may lead us to reject a weak version of the theory when a stronger version sits around the conceptual corner, waiting to be discovered. For the present, we prefer to build rather than to destroy (Newell, 1990). We are more interested in what ECTVA can do than what it cannot do. However, ECTVA is built from powerful components. TVA and EBRW provide excellent quantitative accounts of many different phenomena in the attention literature and the categorization literature, so the components of our theory have not gone untested.

The virtue of modularity in theorizing is the possibility of developing a general theory of cognition that is integrative and cumulative (Anderson, 1993; Logan, 2001; Meyer & Kieras, 1997a; Newell, 1990; Posner, 1982). The divide-and-conquer strategy that dominates much of current research has clarified different aspects of the blooming, buzzing confusion that surrounds us, but it has not yet made clear how the different aspects are related. Viewed collectively, the special-purpose theories may be as confusing as the bloom and the buzz they were meant to clarify. We proposed one specific integration, combining TVA and EBRW to form ECTVA. Some of the details may be wrong, but we hope that the basic idea—that an executive process programs a programmable subordinate—may prove useful in future attempts at integration.

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Appendix A

Simulations of Parallel and Serial Processing

To simulate serial and parallel processing in the theory of visual attention (TVA), we assumed there were two stimuli, S1 and S2, that each took two values. S1 was represented by two η values: $\eta(x, 1)$ and $\eta(x, 2)$. S2 was also represented by two η values: $\eta(y, 1)$ and $\eta(y, 2)$. On each trial, one value was "turned on" for each stimulus, by setting the corresponding η value high (e.g., to 10.0). The other value of each stimulus was "turned off" by setting η low (e.g., to 1.0). We used all four possible combinations of S1 and S2, simulating each one 40,000 times.

We set β high (to 1.0) for both values of each stimulus. To generate processing rates, we multiplied η values by β values and multiplied that product by the attention weights on the relevant objects, using relative attention weights (Equation 7) if TVA's capacity was limited and absolute attention weights (Equation 6) if TVA's capacity was unlimited. The attention weights were determined by two priority parameters, π_{top} and π_{bottom}, for the stimulus-set categories "top" and "bottom," respectively, and by four η values for the similarities between S1 and S2 and the stimulus-set categories (i.e., $\eta[S1, top]$, $\eta[S1, bottom]$, $\eta[S2, top]$, and $\eta[S2, bottom]$). To present S1 in the top position and S2 in the bottom position, we set $\eta(S1, top)$ and $\eta(S2, bottom)$ high (i.e., 10.0) and $\eta(S1, bottom)$ and $\eta(S2, top)$ low (i.e., to 1.0). The feature-catch parameters, c, were set to 1.0, so they disappeared from Equations 13 and 14.

We modeled serial and parallel processing by manipulating the attention weights through the priority parameter, π. In parallel processing, both π_{top} and π_{bottom} were set high (i.e., to 1.0) so that S1 and S2 would have equal attention weights (both = 0.5). In serial processing, we set π_{top} high (1.0) and π_{bottom} low (0.1) to select S1 before S2. Then, after R1 was selected, we set π_{top} low (0.1) and π_{bottom} high (1.0) to select S2. In all other respects (i.e., in terms of ηs and βs), serial processing was the same as parallel processing.

We manipulated capacity limitations in response selection by varying α in Equation 15. We set α to 0.3 when response-selection capacity was limited and to 0.0 when response-selection capacity was unlimited. We held K constant at 3.0 because this value produced human-like accuracies.

In each simulated trial, we began by setting the random-walk counters to 0. Then we calculated processing rates from ηs, βs, and πs, using Equation 7 if TVA capacity was limited and Equation 6 if TVA capacity was unlimited. We used the processing rates to compute categorization probabilities, following Equation 13, and we used those probabilities to choose a categorization at random. The counter corresponding to the chosen categorization was incremented by 1, and the threshold was tested by comparing the number of categorizations in the highest counter with the number in the second highest counter and determining whether the difference equaled the criterion, K. If the difference was smaller than the criterion, the process repeated. Another categorization was chosen and added to its counter, and the threshold was tested again. If the difference was equal to or greater than the criterion, K, the response corresponding to that counter was "executed." As soon as the first response was executed, the counters were inhibited completely (all of their values were multiplied by 0), π was changed if processing was serial, and processing rates were calculated once again. The chosen responses were compared with the correct responses to score accuracy. Order mattered, as discussed in the text of the article.

We simulated Reaction Time 1 (RT1) by simulating T_{step} (Equation 15) on each step of the random walk and summing the values over the number of steps required to terminate the walk (to exceed K). Like Nosofsky and Palmeri (1997), we held α constant and let T_{first} (Equation 2, i.e., $1/\Sigma\Sigma\ v(z, j)$) vary randomly. That is, we sampled a value at random from an exponential distribution with a rate parameter equal to the reciprocal of Equation 2 (i.e., $\Sigma\Sigma\ v(z, j)$), and we added the sampled value to α to produce T_{step} for each step until the walk terminated. We simulated RT2 in a similar manner. Because S1 and S2 were simultaneous (stimulus onset asynchrony = 0), RT2 included RT1 as well as the time required to choose the second response. Finally, we transformed model time into milliseconds using a regression equation with an intercept and a slope that were the averages of the regression equations used to simulate the experiments: $RT_{observed} = 455 + 122(RT_{simulated})$.

(Appendixes continue)

Appendix B

Method and Inferential Statistics for Experiment 1

Subjects

The subjects were 16 volunteers from the university community who were paid $10 for completing two sessions.

Apparatus and Stimuli

The stimuli were displayed on Gateway 2000 Crystalscan 1024 NI monitors, controlled by Gateway 2000 486 computers. Responses to the first stimulus (S1) were collected from the period (.) and slash (/) keys; responses to the second stimulus (S2) were collected from the *z* and *x* keys. Timing was accurate to 1 ms. The stimulus onset asynchronies (SOAs) were 0, 100, 300, or 900 ms. The stimuli were the digits 1, 2, 3, 4, 6, 7, 8, and 9 (5 was excluded).

The fixation display consisted of four dashes (-) arranged in two rows (see Figure 1). Each row contained two dashes separated by three blank spaces. The top row began on row 13 and column 37 of the 24 row × 80 column IBM text screen. The bottom row began on row 14 and column 37. The second display contained two digits if SOA was 0 and one if SOA was greater than 0. In the one-digit display the character appeared in the top row indicated by the fixation field, in a position that was centered between the two dashes (row 13, column 38). In the two-digit display the top digit remained the same and appeared in the same position. The bottom character appeared immediately below it, in row 14, column 38. Viewed at a distance of 60 cm, the fixation display subtended 1.53 × 1.43 degrees of visual angle. Each digit subtended 0.48 × 0.28 degrees of visual angle. The fixation display was exposed for 500 ms. If SOA was greater than 0, the first digit was exposed for SOA ms, and then the second digit appeared, and the two remained on the screen for 1,000 ms. The display was then extinguished and replaced by a blank screen for a 3,500-ms intertrial interval.

Procedure

Each subject served in two sessions, one in a dual-task condition and one in a single-task condition. The basic design for each session involved 256 trials (8 digits for S1 × 8 digits for S2 × 4 SOAs). There were two replications of this design, for a total of 512 trials each session. In the dual-task condition, subjects responded to both digits, using their right hand for the top digit (index finger on period key for greater than 5, middle finger on slash key for less than 5) and their left hand for the bottom digit (index finger on *x* for greater than 5, middle finger on *z* for less than 5). In the single-task condition, the displays were exactly the same (i.e., both S1 and S2 were presented on each trial), but subjects responded only to the top digit, which appeared first when SOA was greater than 0, using the index and middle fingers of their right hand to report magnitude. Half of the subjects had the dual-task session before the single-task session, and the other half had the opposite.

Subjects were given verbal instructions that told them which keys to press in response to S1 and S2. Task 1 was emphasized in the dual-task conditions. Subjects were told to respond to it as quickly as possible and not to wait for S2. They were told to rest their hands on the response keys throughout the experiment. They were allowed brief rest breaks throughout the experiment.

Design

Mean reaction times (RTs) and accuracy scores were analyzed separately for Responses 1 and 2 (R1 and R2). The data for R1 were analyzed in 2 (single vs. dual task) × 2 (congruency: same or different) × 4 (SOA: 0, 100, 300, or 900 ms) analyses of variance (ANOVAs). The data for R2 were analyzed in 2 (congruency: same or different) × 4 (SOA) ANOVAs. Unless stated otherwise, we used $p < .05$ as our criterion for statistical reliability.

Results

The ANOVAs on the RT data supported the conclusions drawn in the text of the article. The basic psychological refractory period effects were evident as a main effect of SOA in the RT2 ANOVA, $F(3, 45) = 228.61$, $MSE = 3{,}333.49$, and a null effect of SOA in the RT1 ANOVA, $F(3, 45) = 1.11$, $MSE = 8{,}588.44$. The concurrence cost was evident in a main effect of dual versus single in the RT1 ANOVA, $F(1, 15) = 58.11$, $MSE = 35{,}548.97$. Crosstalk effects on RT1 were evidenced by a main effect of congruency, $F(1, 15) = 5.41$, $MSE = 2{,}017.66$. The interaction between dual versus single task and congruency was significant, $F(1, 15) = 7.72$, $MSE = 2{,}135.47$. Planned comparisons showed that the congruency effect was significant in dual-task RT1, $F(1, 15) = 12.60$, $MSE = 2{,}135.47$, but not in single-task RT1 ($F < 1$). The only other significant effect in the RT1 analysis was the interaction among dual versus single task, congruency, and SOA, $F(3, 45) = 5.21$, $MSE = 907.57$. In the RT2 ANOVA, there was also a main effect of congruency, $F(1, 15) = 82.62$, $MSE = 3{,}134.93$, and an interaction between congruency and SOA, $F(3, 45) = 13.25$, $MSE = 1{,}718.96$.

The accuracy data are presented in Table B1. The accuracy analyses revealed nothing inconsistent with the RT analyses. In the R1 analysis the only significant effects were the main effect of dual versus single task, $F(1, 15) = 7.50$, $MSE = 75.20$; the main effect of SOA, $F(3, 45) = 4.30$, $MSE = 5.68$; and the interaction between dual versus single task and SOA, $F(3, 45) = 9.67$, $MSE = 5.67$. In the R2 analysis, only the main effect of SOA was significant, $F(3, 45) = 9.59$, $MSE = 7.92$.

We used all possible combinations of digits for S1 and S2, so some trials involved identical stimuli, some involved response repetitions, and some involved incongruent stimuli. Equation 17 says that crosstalk depends on response repetition rather than stimulus repetition, so we divided our data into identical, repetition, and incongruent trials to test that prediction. For the single-task condition, RTs on identical trials ($M = 571$ ms) were slightly slower than RTs on repetition ($M = 566$ ms) and incongruent trials ($M = 565$ ms). For dual-task RT1, identical trials were faster than repetition trials, which were faster than incongruent trials (*M*s = 719, 736, and 760 ms, respectively). The same was true for dual-task RT2 (M for identical trials = 706 ms, M for repetition trials = 759 ms, and M for

Table B1
Mean Percentage Correct in Experiment 1 as a Function of Single- Versus Dual-Task Conditions, Congruency, and Stimulus Onset Asynchrony (SOA)

SOA (ms)	Single task		Dual task	
	Congruent	Incongruent	Congruent	Incongruent
0	96.2	96.9	94.9	94.9
100	97.1	98.1	95.4	93.4
300	97.2	98.3	95.4	95.6
900	98.8	97.9	94.6	95.8

incongruent trials = 835 ms). We assessed the statistical reliability of these effects by computing Fisher's least significant difference test ($p < .05$) for the highest order interaction in a 3 (single task vs. RT1 vs. RT2) × 3 (identical vs. repetition vs. incongruent) × 4 (SOA: 0, 100, 300, 900 ms) ANOVA. We used the critical value of 25 ms to compare RTs in the identical and repetition conditions against RTs in the incongruent condition, to see if the congruency effect depended on stimulus repetition. By this criterion, none of the congruency effects was significant at any SOA in the single-task condition. In the RT1 data, the congruency effect was significant at the 0- and 100-ms SOA for the repetition condition (differences = 47 and 31 ms, respectively) and at the 0- and 100-ms SOA for the identical condition (differences = 99 and 76 ms, respectively). In the RT2 data, the congruency effect was significant at the 0-, 100-, and 300-ms SOAs for the repetition condition and at all SOAs for the identical condition. Thus, the congruency effect can be obtained in both RT1 and RT2 data without stimulus repetition.

Appendix C

Simulation of Experiment 1

We simulated Experiment 1 using the same-task-set parameter values that appear in Table C1. The dual-task conditions used those parameters exactly. The single-task conditions used the same η values as the dual-task conditions, but the β and π parameters were different. Single-task βs were set high (1.0) for Stimulus 1 (S1) magnitude, low (0.1) for S1 parity, and low (0.1) for both dimensions of S2. We set π high (1.0) for S1 and low (0.1) for S2 (i.e., π_{top} high and π_{bottom} low), and the simulated single-task trial ended when Task 1 was finished. We used four stimulus onset asynchronies (SOAs; 0, 1.14, 3.41, and 10.23) that corresponded to 0, 100, 300, and 900 ms in real time. We simulated 10,000 trials in each of the 16 possible combinations of S1 and S2 for each of the four SOAs in single-task and dual-task conditions.

We implemented set-switching times and response competition in these simulations. In single-task conditions, we assumed that no parameters had to be changed before each trial, because π and β parameters from the last trial could carry over to the next one. In dual-task conditions, we assumed that one parameter had to be changed before Task 1 could begin (i.e., π had to be set for S1). To implement this, we took one sample from an

Table C1
Values of the TVA Parameters Used in the Simulations of Crosstalk and Set Switching

TVA parameter S1					TVA parameter S2				
Same task set									
η(*S1, large*)	10	10	1	1	η(*S2, large*)	10	10	1	1
η(*S1, small*)	1	1	10	10	η(*S2, small*)	1	1	10	10
η(*S1, odd*)	10	1	10	1	η(*S2, odd*)	10	1	10	1
η(*S1, even*)	1	10	1	10	η(*S2, even*)	1	10	1	10
β_{large}	1.0	1.0	1.0	1.0	β_{large}	1.0	1.0	1.0	1.0
β_{small}	1.0	1.0	1.0	1.0	β_{small}	1.0	1.0	1.0	1.0
β_{odd}	0.1	0.1	0.1	0.1	β_{odd}	0.1	0.1	0.1	0.1
β_{even}	0.1	0.1	0.1	0.1	β_{even}	0.1	0.1	0.1	0.1
η(*S1, top*)	10	10	10	10	η(*S2, top*)	1	1	1	1
η(*S1, bot*)	1	1	1	1	η(*S2, bot*)	10	10	10	10
π_{top}	1.0	1.0	1.0	1.0	π_{top}	0.1	0.1	0.1	0.1
π_{bot}	0.1	0.1	0.1	0.1	π_{bot}	1.0	1.0	1.0	1.0
Different task set									
η(*S1, large*)	10	10	1	1	η(*S2, large*)	10	10	1	1
η(*S1, small*)	1	1	10	10	η(*S2, small*)	1	1	10	10
η(*S1, odd*)	10	1	10	1	η(*S2, odd*)	10	1	10	1
η(*S1, even*)	1	10	1	10	η(*S2, even*)	1	10	1	10
β_{large}	1.0	1.0	1.0	1.0	β_{large}	0.1	0.1	0.1	0.1
β_{small}	1.0	1.0	1.0	1.0	β_{small}	0.1	0.1	0.1	0.1
β_{odd}	0.1	0.1	0.1	0.1	β_{odd}	1.0	1.0	1.0	1.0
β_{even}	0.1	0.1	0.1	0.1	β_{even}	1.0	1.0	1.0	1.0
η(*S1, top*)	10	10	10	10	η(*S2, top*)	1	1	1	1
η(*S1, bot*)	1	1	1	1	η(*S2, bot*)	10	10	10	10
π_{top}	1.0	1.0	1.0	1.0	π_{top}	0.1	0.1	0.1	0.1
π_{bot}	0.1	0.1	0.1	0.1	π_{bot}	1.0	1.0	1.0	1.0

Note. Each row represents a parameter, and each column of numbers represents the values of the parameters for a particular instantiation of Stimulus 1 (S1) or S2. In all of the simulations, α was held constant at 0.3, K was held constant at 3.0, and the response-counter inhibition parameter was held constant at 0.9. TVA = theory of visual attention; bot = bottom.

(*Appendixes continue*)

exponential distribution with a rate parameter of 1.0 and added it to Reaction Time 1 (RT1). We assumed that one parameter had to be changed before Task 2 could begin (i.e., π had to be set to select S2). We assumed that the βs for Task 1 and Task 2 were in place before S1 and S2 appeared and that the βs for S1 remained in place throughout Task 2. We assumed that the response counters had to be inhibited (their values multiplied by 0.1) before Task 2 could begin, and we assumed this went on in parallel with parameter changing. The time to inhibit the counter was sampled from the same exponential distribution that was used for the parameter changing times. Set-switching time for Task 2 was the maximum of the time to change π and the time to inhibit the counters. To implement this, we sampled two values from the same exponential distribution and took the largest value as the set-switching time. We assumed that set switching began as soon as R1 was executed, so when Task 2 began RT2 was set to RT1 − SOA + (set switching and counter inhibition time) or 0, whichever was greater. The rate parameter for the set-switching and counter-inhibiting exponential distribution was fixed at 1.0 for all simulations.

In order to scale the simulated RTs to the data from Experiment 1, we first correlated the simulated and observed RTs at SOA = 0. We used the regression equation from this correlation to determine the SOA values we used to simulate SOA > 0. The correlation between simulated and observed RTs at SOA = 0 was 0.993. The regression equation was $RT_{observed} = 436 + 88(RT_{simulated})$. Using this equation, we simulated the 100-, 300-, and 900-ms SOAs with simulated SOAs of 1.14, 3.41, and 10.23. Then we used the regression equation once again to transform the simulated RTs to the millisecond scale. Finally, we correlated the simulated and observed RTs over all conditions and SOAs. The result was $r = .9561$. The mean simulated RTs, transformed to the millisecond scale, appear in Figure 11. The simulated accuracies appear in Table C2.

Table C2
Accuracy Data (Percentage Correct) for the Simulations of Experiment 1 as a Function of Single- Versus Dual-Task Conditions, Congruency, and Stimulus Onset Asynchrony (SOA)

SOA (ms)	Single task: Cong	Single task: Incong	Dual task R1: Cong	Dual task R1: Incong	Dual task R2: Cong	Dual task R2: Incong
0	99.9	99.8	99.9	97.7	99.9	91.8
100	99.9	99.9	99.9	98.9	99.9	91.7
300	99.9	99.9	99.8	99.6	99.9	91.7
900	99.9	99.9	99.8	99.8	99.9	91.6

Note. R = response; Cong = congruent; Incong = incongruent.

Appendix D

Method and Inferential Statistics for Experiment 2

Subjects

There were 96 subjects, divided into six groups of 16. The subjects were students from an introductory psychology course who participated to fulfill course requirements.

Apparatus and Stimuli

The stimuli were displayed on the same computers used in the previous experiments. Responses to the first stimulus were collected from the comma (,), period (.), and slash (/) keys; responses to the second stimulus were collected from the *z*, *x*, and *c* keys. The stimulus onset asynchronies (SOAs) were 0, 100, 300, or 900 ms.

For half of the subjects, the color was presented first; for the other half, the word was presented first. The color bars were formed by concatenating seven block characters (ASCII No. 219). They appeared in rows 12 and 14 of the IBM text screen, beginning in column 34. They were colored red (IBM 12), blue (IBM 9), or green (IBM 10). The words *RED, BLUE,* and *GREEN* appeared in white (IBM 15) between the color bars, in row 13 of the IBM text screen. The words were left justified, beginning in column 35. Viewed at a distance of 60 cm, each color bar subtended 0.76 × 2.10 degrees of visual angle. The entire color-bar and word display subtended 2.29 × 2.10 degrees. The words subtended 0.48 × 0.86 (RED), 1.15 (BLUE), or 1.43 (GREEN) degrees.

Each trial involved three displays if SOA was 0 and four displays if SOA was greater than 0. The first display in all conditions contained a plus sign centered in the screen (row 13, column 37) to serve as a fixation point and a warning stimulus. It was exposed for 500 ms. Then it was extinguished and replaced immediately by Stimuli 1 and 2 (S1 and S2) if SOA was 0 or by S1 if SOA was greater than 0. If SOA was zero, S1 and S2 were exposed for 1,000 ms, and then the screen went blank for a 3,500-ms intertrial interval. If SOA was greater than 0, S1 remained exposed until SOA ms elapsed, and then a display containing both S1 and S2 was exposed

Table D1
Mean Percentage Correct in the Color and Word Tasks of Experiment 2 as a Function of Single- Versus Dual-Task Conditions, Congruency, and Stimulus Onset Asynchrony (SOA)

SOA (ms)	Single 1	Single 2	Dual 1	Dual 2
Color task: Congruent				
0	97.7	96.0	92.8	93.0
100	97.7	94.2	92.6	91.9
300	97.8	94.8	91.4	91.8
900	98.2	95.9	92.0	92.3
Color task: Incongruent				
0	96.8	95.1	89.8	87.6
100	98.3	95.4	90.1	91.1
300	98.1	95.4	91.3	89.1
900	97.8	96.0	89.4	89.6
Word task: Congruent				
0	96.9	98.5	93.0	92.8
100	98.7	97.8	91.9	92.6
300	97.6	97.9	91.8	91.4
900	98.8	98.1	92.3	92.0
Word task: Incongruent				
0	97.4	97.3	87.6	89.8
100	98.1	98.0	91.1	90.1
300	98.1	98.1	89.1	91.3
900	98.7	98.4	89.6	89.4

Table D2
Results of Analyses of Variance on Reaction Times for the Color and Word Tasks in Experiment 2

Effect	*MSE*	*df*	*F*
	Color responses		
Dual vs. single (D)	347,143.98	1, 60	78.58**
Task 1 vs. Task 2 (T)	347,143.98	1, 60	1.04
D × T	347,143.98	1, 60	1.97
Congruency (C)	5,025.60	1, 60	295.45**
C × D	5,025.60	1, 60	166.88**
C × T	5,025.60	1, 60	41.13**
C × D × T	5,025.60	1, 60	16.01**
SOA (S)	6,891.54	3, 180	63.69**
S × D	6,891.54	3, 180	40.31**
S × T	6,891.54	3, 180	94.78**
S × D × T	6,891.54	3, 180	65.57**
C × S	2,131.44	3, 180	51.53**
C × S × D	2,131.44	3, 180	36.63**
C × S × T	2,131.44	3, 180	0.31
C × S × D × T	2,131.44	3, 180	2.26
	Word responses		
Dual vs. single	409,329.13	1, 60	60.02**
Task 1 vs. Task 2	409,329.13	1, 60	0.01
D × T	409,329.13	1, 60	0.03
Congruency	6,776.28	1, 60	180.59**
C × D	6,776.28	1, 60	122.92**
C × T	6,776.28	1, 60	6.50*
C × D × T	6,776.28	1, 60	0.68
SOA	9,927.43	3, 180	39.65**
S × D	9,927.43	3, 180	23.77**
S × T	9,927.43	3, 180	64.96**
S × D × T	9,927.43	3, 180	42.43**
C × S	2,179.84	3, 180	54.06**
C × S × D	2,179.84	3, 180	44.26**
C × S × T	2,179.84	3, 180	0.45
C × S × D × T	2,179.84	3, 180	0.63

Note. SOA = stimulus onset asynchrony.
* $p < .05$. ** $p < 01$.

for 1,000 ms. The displays looked as if S1 remained on the screen for the whole trial, being joined by S2 after the SOA elapsed.

Procedure

The basic design involved 36 trials: three colors (or words) for S1 × three words (or colors) for S2 × four SOAs (0, 100, 300, or 900 ms). All possible combinations of colors and words were used with equal frequency, so one third of the trials were congruent, and two thirds were incongruent. The experiment consisted of 12 replications of the basic 36-trial design, for a total of 432 trials.

There were six groups of subjects. For three groups (i.e., half of the subjects), the color bars appeared before the word (if SOA > 0), while for the other three groups, the word appeared before the color bars. Within each set of three groups, one group (the *dual-task* group) responded to both S1 and S2, one group (the *single-task S1* group) responded to S1 and ignored S2, and one group (the *single-task S2* group) responded to S2 and ignored S1.

Subjects always responded to S1 with their right hand and to S2 with their left hand, even in the single-task condition (i.e., single-task subjects who responded to S1 did so with their right hands; single-task subjects who responded to S2 did so with their left hands). The assignment of keys to stimuli was counterbalanced between subjects. There were four mapping rules: RBG–RBG, RBG–GBR, GBR–GBR, and GBR–RBG, where *R* is red; *G* is green; *B* is blue; and the left-to-right order corresponds to key presses from the left ring, left middle, left index, right index, right middle, and right ring fingers.

Design

Mean reaction times (RTs) and accuracy data were analyzed in 2 (dual vs. single task) × 2 (Task 1 vs. Task 2) × 2 (congruent vs. incongruent) × 4 (SOA: 0, 100, 300, or 900 ms) analyses of variance (ANOVAs). Data from the color naming task were analyzed separately from the data from the word reading task. Thus, Task 1 versus Task 2 was a between-subjects factor. Subjects who responded to the word for Task 1 and the color for Task 2 contributed their Task 1 data to the word analysis and their Task 2 data to the color analysis. Dual versus single task was also a between-subjects factor. Stroop congruency and SOA were within-subjects factors.

Results

The accuracy data from Experiment 2 are presented in Table D1. The ANOVAs on the RT data and the accuracy data are presented in Table D2.

Table D3
Results of Analyses of Variance on Accuracy Scores for the Color and Word Tasks in Experiment 2

Effect	*MSE*	*df*	*F*
	Color responses		
Dual vs. single (D)	174.60	1, 60	23.00**
Task 1 vs. Task 2 (T)	174.60	1, 60	1.47
D × T	174.60	1, 60	0.78
Congruency (C)	23.44	1, 60	7.91**
C × D	23.44	1, 60	8.86**
C × T	23.44	1, 60	0.07
C × D × T	23.44	1, 60	0.43
SOA (S)	11.37	3, 180	0.27
S × D	11.37	3, 180	0.69
S × T	11.37	3, 180	0.45
S × D × T	11.37	3, 180	0.78
C × S	12.94	3, 180	2.54
C × S × D	12.94	3, 180	0.22
C × S × T	12.94	3, 180	0.85
C × S × D × T	12.94	3, 180	0.49
	Word responses		
Dual vs. single	147.16	1, 60	43.15**
Task 1 vs. Task 2	147.16	1, 60	0.03
D × T	147.16	1, 60	0.03
Congruency	22.94	1, 60	8.66**
C × D	22.94	1, 60	8.45**
C × T	22.94	1, 60	0.13
C × D × T	22.94	1, 60	0.34
SOA	10.08	3, 180	0.99
S × D	10.08	3, 180	0.65
S × T	10.08	3, 180	1.14
S × D × T	10.08	3, 180	0.05
C × S	11.47	3, 180	1.61
C × S × D	11.47	3, 180	0.82
C × S × T	11.47	3, 180	0.32
C × S × D × T	11.47	3, 180	1.60

Note. SOA = stimulus onset asynchrony.
** $p < .01$.

(*Appendixes continue*)

The basic psychological refractory period results were evidenced in the main effect of SOA and the interactions between SOA and Task 1 versus Task 2 and between SOA and dual versus single task, which were highly significant.

Concurrence costs were evident in the main effect of dual versus single task, which was highly significant for both color and word responses. The concurrence costs in RT1 were supported by highly significant contrasts based on the error term for the interaction between dual versus single task and Task 1 versus Task 2: for colors, $F(1, 180) = 27.82$, $MSE = 347{,}143.98$; for words, $F(1, 180) = 31.39$, $MSE = 409{,}329.13$.

Crosstalk was evidenced by the main effect of congruency, which was significant for both color and word responses. The greater crosstalk in dual- than in single-task conditions is evidenced by the interaction between congruency and dual versus single task, which was significant in both analyses. The theoretically important crosstalk effects on dual-task RT1 were evidenced by contrasts based on the error term from the interaction among congruency, dual versus single task, and Task 1 versus Task 2. The contrast was highly significant for colors, $F(1, 60) = 96.95$, $MSE = 5{,}025.60$, and for words, $F(1, 60) = 124.56$, $MSE = 6{,}776.28$. Finally, Fisher's least significant difference test for $p < .05$ was computed from the highest order interaction ($df = 180$). By this criterion, differences larger than 16 ms were significant in each data set.

The ANOVAs on the accuracy data are presented in Table D3. The accuracy ANOVAs were consistent with the RT ANOVAs. There was no suggestion of a speed–accuracy tradeoff.

Appendix E

Simulation of Experiment 2

In simulating Experiment 2, we represented only one dimension for each stimulus, and we used different, nonoverlapping dimensions for colors and words. Thus, if Stimulus 1 (S1) was the word "*red*," $\eta(S1, red)$ would be set high (to 10.0), and $\eta(S1, blue)$ and $\eta(S1, green)$ would be set low (to 1.0). If S2 was the color green, $\eta(S2, green)$ would be set high (to 10.0), and $\eta(S2, red)$ and $\eta(S2, blue)$ would be set low (to 1.0). As before, $v(x, i)$s were calculated separately for each stimulus but were combined in the calculation of categorization probability, as in Equation 17. Thus, there was no overlap between tasks in stimulus representation, but there was overlap at the level of categorization.

We simulated dual-task conditions in the serial mode. We set β for Task 1 and Task 2 categorizations high (1.0) during both tasks. We ensured serial processing by setting π high (1.0) for S1 and low (0.1) for S2 during Task 1 and low (0.1) for S1 and high (1.0) for S2 during Task 2.

We simulated single-task responses using the same η values as the dual-task simulations. To simulate responses to S1, we set β high (1.0) for S1 classifications during Task 1 and low (0.1) otherwise. To respond to S1, we set π high (1.0) for S1 and low (0.1) for S2. In all other respects, single-task responses to S1 were simulated in the same way as dual-task responses to S1, except that no parameters were changed before S1 in the single-task condition (vs. one in the dual-task condition), and the response selection addressed three counters (vs. six in the dual-task condition).

We simulated single-task responses to S2 by setting β high (1.0) for S2 categorizations and low (0.1) for all others and by setting π high (1.0) for S2 and low (0.1) for S1. Our simulations began with the presentation of S1 if the stimulus onset asynchrony (SOA) was greater than 0 and with S1 and S2 if SOA was 0. If SOA was greater than 0, we let the counters accumulate categorizations throughout the SOA, although the rate was reduced because β was low for S1 categorizations and π was low for S1. When S2 was presented, the counters were inhibited, as they were before dual-task responses to S2, and the counters accumulated categorizations until a response was selected. There was no set-switching time added to single-task RT2; π and β remained the same throughout.

We simulated performance at four SOAs (0, 0.57, 1.72, and 5.17 model units, which corresponded to 0, 100, 300, and 900 ms) in all nine combinations of colors and words. One third of the simulated trials were congruent (color = word), and two thirds were incongruent (color ≠ word). We simulated 10,000 trials in each combination of these conditions. We ran three separate simulations: one in dual-task conditions, one in single-task conditions responding to S1, and one in single-task conditions responding to S2.

We set SOAs by correlating observed and predicted reaction times (RTs) at SOA = 0. The correlation between color responses and ECTVA predictions was .9704; the regression equation was $RT_{observed} = 372 + 175(RT_{simulated})$. The correlation between word responses and ECTVA was .9269, and the regression equation was $RT_{observed} = 473 + 149(RT_{simulated})$. We used the regression equation from the color correlation to generate SOAs and predicted RTs in milliseconds. The full set of predicted RTs, depicted in Figure 11, were correlated strongly with the color data ($r = .9375$) and the word data ($r = .8797$). The correlation between the color data and word data was $r = .9816$. The predicted accuracy scores are presented in Table E1.

Table E1
Accuracy Data (Percentage Correct) for the Simulations of Experiment 2 as a Function of Single- Versus Dual-Task Conditions, Congruency, and Stimulus Onset Asynchrony (SOA)

SOA (ms)	R1 single		R2 single		R1 dual		R2 dual	
	Cong	Incong	Cong	Incong	Cong	Incong	Cong	Incong
0	99.9	99.8	99.9	99.8	99.8	97.7	99.8	91.8
100	99.8	99.8	99.6	99.1	99.8	98.7	99.8	92.2
300	99.8	99.8	99.6	99.1	99.8	99.2	99.8	92.2
900	99.8	99.9	99.7	98.9	99.8	99.7	99.8	92.2

Note. R1 and R2 = Responses 1 and 2; Cong = congruent; Incong = incongruent.

Appendix F

Method and Inferential Statistics for Experiment 3

Subjects

Sixteen subjects participated in this experiment. All were undergraduate students who were native speakers of English. Each subject was paid $20 to participate in four sessions.

Apparatus and Stimuli

The apparatus was the same as in Experiment 2. Subjects responded to the top stimulus by pressing the period or slash key and to the bottom stimulus by pressing the *z* or *x* key. Stimulus onset asynchrony (SOA) was 0, 400, or 1,000 ms.

The stimuli consisted of 96 pictures taken from Snodgrass and Vanderwart (1980) and 96 words that named the objects. They were drawn in black on a white background. Half of the pictures were of animals, and half were of nonanimals. The animal names were written in lowercase. They had a mean length of 5.3 letters (SD = 1.92); a mean written frequency of 28.9 per million (SD = 50.55; Francis & Kucera, 1982); and subtended, on average, 0.8 degrees vertically (SD = 0.08 degrees) and 3.4 degrees horizontally (SD = 1.30 degrees), viewed at a distance of 60 cm. Nonanimal names had a mean length of 5.3 letters (SD = 1.89) and a mean written frequency of 28.8 per million (SD = 28.53). On average, nonanimal names also subtended 0.8 degrees vertically (SD = 0.07 degrees) and 3.4 degrees horizontally (SD = 1.27 degrees). The mean size of the animal pictures was 3.6 degrees vertically (SD = 0.88 degrees) and 3.4 degrees horizontally (SD = 0.69 degrees), while the mean size of the nonanimal pictures was 3.6 degrees (SD = 0.75 degrees) × 3.1 degrees (SD = 0.81 degrees). We fixed the distance between the bottom edge of the top picture or word

Table F1
Accuracy for R1 and R2 in the Form Judgment Tasks of Experiment 3 as a Function of Stimulus Onset Asynchrony (SOA), Task Set, Form Congruence, and Animacy Congruence

	Form cong		Form incong	
SOA (ms)	Animacy cong	Animacy incong	Animacy cong	Animacy incong
	R1: Same task set			
0	93.8	94.7	96.4	95.8
400	96.9	95.8	97.8	97.5
1,000	97.8	97.7	98.6	97.2
	R1: Different task set			
0	93.8	92.8	93.0	92.0
400	95.0	93.4	95.0	94.1
1,000	94.1	94.2	93.1	93.3
	R2: Same task set			
0	94.7	95.5	94.5	93.4
400	95.3	94.5	93.9	95.5
1,000	96.7	95.5	95.6	96.1
	R2: Different task set			
0	93.9	89.4	91.4	88.9
400	94.5	85.9	91.9	88.3
1,000	92.3	89.8	93.4	93.1

Note. All numbers are percentages. R1 and R2 = Responses 1 and 2; cong = congruent; incong = incongruent.

Table F2
Results of Analyses of Variance on Mean RT1, Mean RT2, and Percentage of Correct Responses for the Form Judgment Tasks of Experiment 3

Effect	*MSE*	*df*	*F*
	RT1		
Task set (T)	347,541.34	1, 15	12.61**
Form match (F)	4,186.51	1, 15	24.55**
T × F	2,947.67	1, 15	8.76**
Animacy match (A)	2,990.45	1, 15	1.48
T × A	2,648.32	1, 15	0.58
F × A	1,763.33	1, 15	0.12
T × F × A	2,675.80	1, 15	0.02
SOA (S)	60,334.92	2, 30	2.46
T × S	30,319.73	2, 30	1.83
F × S	7,143.39	2, 30	4.03*
T × F × S	5,149.65	2, 30	5.30*
A × S	4,152.22	2, 30	0.50
T × A × S	4,700.14	2, 30	0.29
F × A × S	2,141.03	2, 30	0.16
T × F × A × S	1,336.17	2, 30	0.04
	RT2		
Task set	811,616.53	1, 15	29.50**
Form match	21,081.82	1, 15	9.41**
T × F	18,947.92	1, 15	20.65**
Animacy match	12,832.29	1, 15	0.02
T × A	13,992.50	1, 15	0.05
F × A	11,389.38	1, 15	5.98*
T × F × A	14,035.25	1, 15	3.69
SOA	12,209.72	2, 30	663.33**
T × S	10,339.63	2, 30	53.52**
F × S	4,178.74	2, 30	29.85**
T × F × S	7,041.53	2, 30	3.12*
A × S	6,698.36	2, 30	0.50
T × A × S	5,927.32	2, 30	0.40
F × A × S	6,147.69	2, 30	0.32
T × F × A × S	6,874.63	2, 30	0.15
	Accuracy		
Task set	208.92	1, 15	4.16
Form match	25.31	1, 15	0.40
T × F	37.23	1, 15	1.63
Animacy match	12.52	1, 15	2.40
T × A	10.55	1, 15	0.12
F × A	6.53	1, 15	0.20
T × F × A	7.13	1, 15	0.66
SOA	51.18	2, 30	2.38
T × S	24.34	2, 30	1.31
F × S	19.66	2, 30	0.66
T × F × S	18.68	2, 30	0.37
A × S	13.68	2, 30	0.31
T × A × S	6.98	2, 30	1.27
F × A × S	9.33	2, 30	0.57
T × F × A × S	4.37	2, 30	0.38

Note. RT = reaction time; SOA = stimulus onset asynchrony.
$*p < .05$. $**p < .01$.

(*Appendixes continue*)

Table F3
Accuracy for R1 and R2 in the Animacy Judgment Tasks of Experiment 3 as a Function of Stimulus Onset Asynchrony (SOA), Task Set, Form Congruence, and Animacy Congruence

	Form cong		Form incong	
SOA (ms)	Animacy cong	Animacy incong	Animacy cong	Animacy incong
	R1: Same task set			
0	95.3	94.8	94.8	90.9
400	95.8	95.6	94.5	94.5
1,000	96.3	95.5	95.2	95.6
	R1: Different task set			
0	95.0	94.4	93.3	92.8
400	96.7	95.6	94.2	94.4
1,000	95.9	94.7	95.5	97.0
	R2: Same task set			
0	97.8	96.3	97.3	93.4
400	98.3	95.8	97.7	97.2
1,000	99.2	95.6	95.1	96.6
	R2: Different task set			
0	96.4	93.4	93.0	90.9
400	95.8	94.2	92.7	93.6
1,000	96.4	92.9	91.3	94.4

Note. All numbers are percentages. R1 and R2 = Response 1 and 2; cong = congruent; incong = incongruent.

and the top edge of the bottom picture or word at 1.43 degrees. Thus, the centers of words were 1.1 degree above or below the center of the screen and the centers of pictures were 2.85 degrees above or below the center of the screen. We were not concerned about the differences in eccentricity between words and pictures because our analyses collapsed across words and pictures.

Procedure

Each subject participated in four experimental sessions. Within a session the basic design involved 48 trial types: animal or nonanimal for stimulus 1 (S1) × animal or nonanimal for S2 × picture or word for S1 × picture or word for S2 × SOA (0, 400, 1,000 ms). Within a session, there were 12 replications of this design, for a total of 576 trials. The 576 trials were divided into six blocks of 96 trials. Subjects were permitted to rest between blocks. The first block in each session was considered practice, so first-block data were not included in the analyses.

The task performed on each stimulus varied across sessions but remained consistent within a session. There were four task combinations: animacy or form judgments on S1 × animacy or form judgments on S2. Two combinations involved the same task set (i.e., animacy–animacy and form–form), and two involved different task sets (i.e., animacy–form and form–animacy). The 96 pictures and 96 words were assigned randomly to trials, except that an object and its name were never presented on the same trial. Pictures and words occurred equally often across trials. No stimulus was repeated within a block.

Each trial began with a fixation display that consisted of two horizontal lines, one above the S1 location and one below the S2 location. The fixation display was presented for 500 ms and then extinguished. If SOA was 0, both S1 and S2 appeared immediately and remained on for 1,000 ms. If SOA was greater than 0, S1 was presented for SOA ms, whereupon it was joined by S2, and both stimuli remained on for 1,000 ms. After 1,000 ms, the screen went blank (white). A 1,500-ms intertrial interval began after subjects responded to both stimuli.

Subjects always responded to S1 with their right hand and to S2 with their left hand. The mapping of keys onto stimuli was counterbalanced

Table F4
Results of Analyses of Variance on Mean RT1, Mean RT2, and Percentage of Correct Responses for the Animacy Judgment Tasks of Experiment 3

Effect	*MSE*	*df*	*F*
	RT1		
Task set (T)	800,047.67	1, 15	6.35*
Form match (F)	11,255.98	1, 15	1.56
T × F	13,071.08	1, 15	2.74
Animacy match (A)	7,221.08	1, 15	2.59
T × A	13,319.23	1, 15	2.02
F × A	12,081.33	1, 15	3.61
T × F × A	7,885.64	1, 15	3.36
SOA (S)	112,393.95	2, 30	3.36*
T × S	17,424.63	2, 30	0.87
F × S	3,379.56	2, 30	3.05
T × F × S	4,921.83	2, 30	0.23
A × S	5,094.54	2, 30	2.99
T × A × S	8,677.42	2, 30	0.45
F × A × S	4,889.62	2, 30	1.05
T × F × A × S	5,172.06	2, 30	0.01
	RT2		
Task set	501,597.13	1, 15	9.00**
Form match	1,599.72	1, 15	49.62**
T × F	2,654.39	1, 15	3.88
Animacy match	6,548.47	1, 15	10.27**
T × A	7,181.17	1, 15	19.23**
F × A	3,577.98	1, 15	16.06**
T × F × A	3,864.51	1, 15	0.76
SOA	16,407.39	2, 30	460.87**
T × S	13,096.97	2, 30	6.79**
F × S	5,374.91	2, 30	0.84
T × F × S	5,674.39	2, 30	1.17
A × S	6,052.61	2, 30	7.06**
T × A × S	3,487.07	2, 30	1.59
F × A × S	2,622.00	2, 30	1.40
T × F × A × S	2,246.84	2, 30	1.04
	Accuracy		
Task set	336.72	1, 15	0.00
Form match	11.11	1, 15	9.85**
T × F	9.17	1, 15	0.45
Animacy match	6.84	1, 15	4.20*
T × A	5.89	1, 15	1.11
F × A	8.61	1, 15	0.37
T × F × A	10.21	1, 15	2.55
SOA	16.88	2, 30	6.32**
T × S	8.25	2, 30	0.08
F × S	9.78	2, 30	4.29*
T × F × S	5.09	2, 30	0.19
A × S	9.72	2, 30	1.72
T × A × S	9.50	2, 30	0.90
F × A × S	13.75	2, 30	2.01
T × F × A × S	7.44	2, 30	0.47

Note. RT = reaction time; SOA = stimulus onset asynchrony.
* $p < .05$. ** $p < .01$.

across subjects. For each task combination, there were four mappings. When subjects made animacy judgments about both stimuli, the mappings were ANAN, ANNA, NANA, and NAAN, where *A* refers to animal and *N* to nonanimal, and the order refers to the four fingers used to respond: the middle and index fingers of the left hand and the index and middle fingers of the right hand, respectively. With form judgments on both stimuli, the mappings were PWPW, PWWP, WPWP, and WPPW, where *W* refers to word and *P* refers to picture. When subjects made animacy judgments on S1 and form judgments on S2, the mappings were PWAN, PWNA, WPAN, and WPNA; when they made form judgments on S1 and animacy judgments on S2 the mappings were ANPW, ANWP, NAPW, and NAWP.

Design

Mean reaction times (RTs) and accuracy scores were analyzed separately for each response (R1 and R2) and for each task (animacy and form judgment) in 2 (task set: same or different) × 2 (form: congruent or incongruent) × 2 (animacy: congruent or incongruent) × 3 (SOA: 0, 400, or 1,000 ms) analyses of variance (ANOVAs).

Results

Form Task

The accuracy data from Experiment 3 are presented in Table F1. The conclusions drawn in the text were supported by inferential statistics. The ANOVAs on RT1, RT2, and accuracy scores are presented in Table F2. In the RT1 ANOVA, only the theoretically relevant effects were significant. There was a significant main effect of task set, indicating set-switching cost. A significant main effect of form congruency and significant interaction between task set and form congruency indicated crosstalk that was modulated by task set. Significant interactions between form congruency and SOA, and among task set, form congruency, and SOA, indicated the modulation of crosstalk by SOA in the same-task-set condition. The change in the form congruency effect over SOA in the same-task-set condition was assessed with Fisher's least significant difference (LSD) test, using the error term from the interaction among task set, form congruency, and SOA. The LSD for $p < .05$ is 37 ms, indicating that the form congruency effect was significant only at the 0-ms SOA.

In the RT2 ANOVA the significant effects supported our conclusions. They included the main effect of task set, the main effect of form congruency, the interaction between task set and form congruency, the main effect of SOA, the interaction between SOA and form congruency, and the interaction between task set and SOA. The only other significant effect was the interaction between form congruency and animacy congruency. The form congruency effect was 113 ms when animacy was congruent and 106 ms when animacy was incongruent.

The change in the form congruency effect with SOA in the same-task-set condition was assessed with Fisher's LSD computed from the interaction among task set, form congruency, and SOA. The LSD for $p < .05$ is 43 ms. By this criterion, the form congruency effect was significant at the 0-ms and the 400-ms SOA.

There were no effects in the ANOVA on the accuracy data that compromised our interpretation of the RTs.

Animacy Task

The accuracy data for the animacy task are presented in Table F3. We assessed the support for the conclusions drawn in the text with inferential statistics. The summary tables for the ANOVAs on the RT1, RT2, and accuracy data are presented in Table F4. The RT1 ANOVA provided mixed support for our conclusions. The main effect of task set was significant, which confirms the set-switching costs, but the main effect of animacy congruency was not significant, neither were any of the interaction effects in which it participated. Undaunted, we carried out our planned assessment of the animacy congruency effects at each SOA with Fisher's LSD calculated from the interaction among task set, animacy congruency, and SOA. The LSD for $p < .05$ is 48 ms. By this criterion, the 71-ms effect at the 0-ms SOA is significant.

The RT2 ANOVA was more supportive of our conclusions. Set-switching cost was confirmed by the main effect of task set. Crosstalk and the dependence of crosstalk on task set were supported by the main effect of animacy, the interaction between animacy and task set, and the interaction between animacy and SOA. Fisher's LSD computed from the interaction among task set, animacy congruency, and SOA yielded an LSD for $p < .05$ of 30 ms. By this criterion, the crosstalk effect was significant at the 0-ms and 400-ms SOAs in the same-task-set condition. The only other remarkable effects were the main effect of form congruency and the interaction between form congruency and animacy congruency. The animacy congruency effect was larger when form was congruent ($M = 94$ ms) than when it was incongruent ($M = 35$ ms).

There was nothing in the accuracy ANOVA that compromised the interpretation of the RT1 and RT2 data.

Appendix G

Simulation of Logan and Schulkind (2000)

We returned to the two-dimensional stimuli used in our previous simulations to simulate set switching and the modulation of crosstalk by task set in Logan and Schulkind's (2000) Experiment 2. The parameter values for the same-task-set condition were the same as those used to simulate Experiment 1. They are presented in Table C1. The parameter values for the different-task-set condition are also presented in Table C1. Note that the only difference between same-task-set and different-task-set conditions is in the β parameters. In the same-task-set conditions, only one parameter (π) had to be set before Task 1 and changed before Task 2. In the different-task-set conditions, three parameters (2 βs and 1 π) had to be set before Task 1 and changed before Task 2.

We used four stimulus onset asynchronies (SOAs): 0.0, 0.96, 2.88, and 8.65 model units, which translated to 0, 100, 300 and 900 ms. We simulated 10,000 trials with each of the 16 possible stimulus 1–stimulus 2 combinations at each SOA in the same-task-set condition and in the different-task-set condition. The simulated accuracy data appear in Table G1.

We set the SOAs by correlating simulated and observed reaction times (RTs) at SOA = 0. That yielded $r = .8839$ and $RT_{observed} = 557 + 104(RT_{simulated})$. The correlation between simulated and observed RTs over all SOAs was $r = .8937$.

(*Appendix continues*)

Table G1
Accuracy Data (Percentage Correct) for the Simulations of Experiment 3 as a Function of Same- Versus Different-Task Set Conditions, Congruency, and Stimulus Onset Asynchrony (SOA)

SOA (ms)	R1 same set		R2 same set		R1 diff set		R2 diff set	
	Cong	Incong	Cong	Incong	Cong	Incong	Cong	Incong
0	99.9	97.7	99.9	91.9	99.8	99.7	99.9	99.5
100	99.8	98.8	99.9	91.7	99.8	99.8	99.9	99.5
300	99.8	99.5	99.9	91.8	99.8	99.8	99.9	99.5
900	99.8	99.8	99.9	91.8	99.8	99.8	99.9	99.5

Note. R1 and R2 = Responses 1 and 2; diff = different; Cong = congruent; Incong = incongruent.

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