A Computational Theory of Executive Cognitive Processes and Human Multiple-Task Performance: Part 1. Basic Mechanisms

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Persistent controversies about human multiple-task performance suggest that research on it will benefit from increased use of precise detailed computational models. Toward this objective, the present report outlines an Executive-Process Interactive Control (EPIC) architecture, which has component modules for processing information at perceptual, cognitive, and motor levels. Based on EPIC, computational models may be constructed to simulate multiple-task performance under a variety of conditions. These models account well for reaction-time data from representative paradigms such as the psychological-refractory-period (PRP) procedure. The attained goodness of fit supports several key conclusions: (1) at a cognitive level, people can apply distinct sets of production rules simultaneously for executing the procedures of multiple tasks; (2) there is no immutable "central" response-selection or decision bottleneck; (3) people's capacity to process information and take action at "peripheral" perceptual-motor levels is limited; (4) to cope with such limits and to satisfy task priorities, flexible scheduling strategies are used; (5) these strategies are mediated by executive cognitive processes that coordinate concurrent tasks adaptively. EPIC's successes suggest that the present theoretical framework may help characterize human multiple-task performance across many domains, including ones that have substantial practical relevance.

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A Computational Theory of Executive Cognitive Processes and Multiple-Task Performance: Part 1. Basic Mechanisms[1]

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Abstract

Persistent controversies about human multiple-task performance suggest that research on it will benefit from increased use of precise computational models. Toward this objective, the present report outlines a comprehensive theoretical framework for understanding and predicting the performance of concurrent perceptual-motor and cognitive tasks. The framework involves an Executive-Process Interactive Control (EPIC) architecture, which has component modules that process information at perceptual, cognitive, and motor levels. On the basis of EPIC, computational models that use a production-system formalism may be constructed to simulate multiple-task performance under a variety of conditions. These models account well for reaction-time data from representative paradigms such as the psychological-refractory-period (PRP) procedure. With modest numbers of parameters, good fits between empirical and simulated reaction times support several key conclusions: (1) at a cognitive level, people can apply distinct sets of production rules simultaneously for executing the procedures of multiple tasks; (2) there is no immutable "central" response-selection or decision bottleneck; (3) people's capacity to process information and take action at "peripheral" perceptual-motor levels is limited; (4) to cope with such limits and to satisfy task priorities, flexible scheduling strategies are used; (5) these strategies are mediated by executive cognitive processes that coordinate concurrent tasks adaptively. The initial success of EPIC and models based on it suggest that they may help characterize multiple-task performance across many domains, including ones that have substantial practical relevance.

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Introduction

People must often perform concurrent tasks, each of which has its own set of stimuli, responses, and stimulus-response associations. For example, consider preparing a meal while tending children, or talking on a cellular telephone while driving a car. A person's ability to cope with such situations depends on how information processing is coordinated across the tasks at hand, and the success or failure of this coordination can have significant consequences under a variety of real-world circumstances. Thus, experimental psychologists, cognitive scientists, and human-factors engineers have devoted substantial effort to studying multiple-task performance. Through their efforts, many important methodological procedures, empirical phenomena, and theoretical constructs have emerged (Atkinson, Hernstein, Lindzey, & Luce, 1988; Damos, 1991; Gopher & Donchin, 1986; Meyer & Kornblum, 1993). What does not yet exist, however, is a precise comprehensive framework for integrating these achievements, deriving veridical quantitative predictions, and making useful practical applications. Instead, heated debates are still under way about the fundamental facts of multiple-task performance and how they should be interpreted theoretically (Allport, 1993; Broadbent, 1993).

The present article takes further steps toward resolving this problematic state of affairs. In doing so, much can be learned about the architecture of the human information-processing system, because the heavy mental workload imposed by multiple-task performance reveals how the system's underlying components are structurally interfaced and what their capacities are. As a result, this may lead to better understanding of performance in many contexts, and to enhanced principles for facilitating people's everyday activities.

Toward these ends, the remainder of the article is organized as follows. First, we review relevant past literature. Next, a comprehensive framework is introduced for characterizing skilled human information processing and action. On the basis of this framework, detailed computational models of multiple-task performance are constructed and tested. To illustrate the utility of such models, we apply them in accounting for some quantitative data from an influential experimental paradigm, the psychological-refractory-period procedure. As shown later, the obtained accounts are good, suggesting that our framework and models have merit. Finally, we discuss how they can be extended in future research, and what their theoretical implications are. A subsequent companion article (Meyer & Kieras, 1997b) pursues these implications and extensions more fully.

Historical Background

Intellectual curiosity about human multiple-task performance has a long and venerable history, which extends back to the Golden Age of Greece (Neumann, 1987; cf. James, 1890). For now, however, several modern theoretical perspectives on this topic are most relevant. These include the single-channel hypothesis, processing-bottleneck models, unitary-resource theory, and multiple-resource theory.

Single-Channel Hypothesis

The single-channel hypothesis stems from research by Telford (1931). He found that if a relatively short interval (0.5 sec or less) separated the stimulus (e.g., auditory tone) for one response (e.g., keypress) from the next stimulus for a subsequent response, then the reaction time (RT) of the subsequent response increased relative to ones with a longer interval (1 sec or more) between stimuli. The RT increase implies that there may be a psychological refractory period analogous to the refractory period between successive neural impulses.

Consistent with this implication, Craik (1948) later reported that when subjects manually tracked moving visual targets, they produced discrete intermittent responses. Each tracking response was separated from the next by about 0.5 sec, even though the target moved continuously. This intermittency, which was confirmed by Vince (1948), led Craik (1948, p. 147) to speculate that:

"... the time lag is caused by the building up of some single 'computing' process which then discharges down the motor nerves ... new sensory impulses entering the brain while this central computing process (is) going on would either disturb it or be hindered from disturbing it by some 'switching' system ... there is a minimum interval within which successive stimuli cannot be responded to."

Further promoting Craik's proposal, Welford (1952, p. 3) stated the single-channel hypothesis as follows:

" ... the refractoriness is in the central mechanisms themselves ... it is due to the processes concerned with two separate stimuli not being able to co-exist, so that the data from a stimulus which arrives while the central mechanisms are dealing with the data from a previous stimulus have to be 'held in store' until the mechanisms have been cleared."

With respect to human multiple-task performance, the import of the single-channel hypothesis is clear. According to it, some mental processes needed for one task must necessarily wait whenever a person engages in another prior task. If so, then this postponement would account directly for breakdowns in performance under conditions of heavy mental workload. The directness, simplicity, and elegance of the account therefore captured the imaginations of numerous theorists following Welford's (1952) publication.

Global single channel. At the same time, the single-channel hypothesis also raised other related questions. For example, what stages of information processing are mediated by the central mechanisms that constitute the single channel? In answer, it might be suggested that either stimulus identification, response selection, movement preparation, or some other intervening mental process is involved.[2] Yet neither Craik (1948) nor Welford (1952) differentiated precisely among these specific possibilities. Rather, they seemed to conclude that all of the mechanisms between stimulus input and response output together constitute a single channel. Thus, we refer to their joint proposals as the *global single-channel hypothesis*.

A major virtue of this hypothesis is that it accounts nicely for Craik's (1948) observations about the intermittency of manual tracking. As mentioned already, he found tracking responses to be separated by temporal intervals of about 0.5 sec each. The lengths of these intervals approximately equal typical summed durations of stimulus identification, response selection, and movement preparation stages in human choice RT (Sternberg, 1969). This is exactly what should happen if all these stages together constitute a single channel through which manual tracking proceeds.

Psychological-refractory-period procedure. Some more tests of the global single-channel hypothesis came from a psychological-refractory-period (PRP) procedure (for excellent reviews, see Bertelson, 1966; Kantowitz, 1974; Pashler, 1994a; Smith, 1967). The PRP procedure involves a series of discrete test trials (Figure 1). On each trial, a warning signal is followed by a stimulus (e.g., visual letter or auditory tone) for the first of two tasks. In response to it, a subject must react quickly and accurately (e.g., by pressing a finger key or saying a word). Soon after the Task 1 stimulus, there is another stimulus for the second task. The sensory modality and semantic category of the Task 2 stimulus may (or may not) differ from those of the Task 1 stimulus. The time between the

[2] Throughout this article, "stimulus identification" refers to perceptual and memory processes that convert an initial sensory code to an abstract symbolic code for a stimulus. "Response selection" refers to a subsequent process that converts the stimulus code to an abstract symbolic code for a physical response, based on some set of innate or previously learned stimulus-response associations. "Movement preparation" refers to a process that converts the symbolic response code to commands for the motor effector system through which the response is physically produced. In terms of these definitions, there may be some cases such that stimulus identification and response selection are either equivalent or closely related processes, leading to systematic patterns of facilitation and interference effects, as found during studies of the Stroop phenomenon (MacLeod, 1991) and stimulus-response compatibility (Kornblum, Hasbroucq, & Osman, 1990). Nevertheless, in many other cases, the stimulus-identification and response-selection stages may be logically distinct and temporally separate from each other, especially if the prevailing stimulus and response codes have no obvious similarities.

two stimuli is the *stimulus-onset asynchrony* (SOA), which typically ranges between zero and 1 sec. In response to the Task 2 stimulus, the subject must again react quickly and accurately. The effector used to make the Task 2 response may (or may not) differ from that for the Task 1 response. In any case, instructions for the PRP procedure typically state that Task 1 should have higher priority than Task 2; they may also urge subjects to make the Task 1 response first.[3] RTs are then measured to determine how much Task 1 actually interferes with the performance of Task 2.

Evidence for and against a global single channel. Using the PRP procedure, researchers initially found putative evidence for the global single-channel hypothesis (e.g., see Davis, 1956, 1957; Vince, 1949; Welford, 1959). Most notably, this hypothesis at first seemed consistent with the relation between Task 2 RTs and SOA, which yielded a so-called *PRP curve* (Figure 2). The PRP curve from some early studies had three theoretically salient features. First, Task 2 RTs were higher at short SOAs than at long SOAs, exhibiting a *PRP effect*, as one would expect with a single channel wherein the Task 1 stimulus temporarily preempts processing of a subsequent Task 2 stimulus. Second, the slope of the PRP curve equaled -1 at short SOAs; for each unit of time that the SOA decreased, the Task 2 RT correspondingly increased. This is what should happen if Task 1 fully occupies the single channel at short SOAs, precluding any progress on Task 2. Third, the PRP effect at the zero SOA equaled the mean Task 1 RT. Apparently, if the Task 2 stimulus arrived at the same moment as the Task 1 stimulus, then processing of the Task 2 stimulus was postponed until the Task 1 response started, as should happen with a global single channel involving all stages of processing for Task 1.

In later research, however, the PRP effect at zero SOA has not always equaled mean Task 1 RTs. Instead, it is sometimes significantly less than the global single-channel hypothesis would predict (e.g., Karlin & Kestenbaum, 1968). This suggests that the single channel does not involve all intervening processes between stimulus and response. Theorists have therefore looked for some specific stage of processing that constrains multiple-task performance. From this search has come the perceptual, response-selection, and movement-production bottleneck models.

Perceptual-Bottleneck Model

Under the perceptual-bottleneck model, the process that identifies stimuli (i.e., converts "raw" sensory representations to symbolic stimulus codes) and determines their meanings is supposedly limited. For concurrent tasks, this limit could force people to deal with only one task at a time. However, the perceptual-bottleneck model makes no specific claims about what, if any, constraints exist on subsequent processes (e.g., response selection and movement preparation) after stimulus identification, so it has also been called *early-selection theory*.

Broadbent's filter theory. One prominent special case of the perceptual-bottleneck model has been introduced by Broadbent (1958). He proposed that stimuli may first enter a sensory buffer in parallel, where their physical features (e.g., locations, intensities, and pitches of sounds) are analyzed and made available to a selective attentional filter. On the basis of these features, past experience, and accompanying task demands, this filter was originally assumed to select particular stimuli for transmission through a limited-capacity channel that identifies them, determines their meanings, and performs other perceptual operations at a fixed maximum rate. Because of this channel's limited capacity, it would reduce the speed with which stimuli for concurrent tasks can be identified, thereby yielding significant between-task interference.

[3] For example, in a study by Pashler (1984, Experiment 1), "the subject was instructed to respond as quickly as possible to both tasks in the two-task blocks, with the restriction that the first stimulus must be responded to before the second" (p. 365). Similarly, in a study by Pashler and Johnston (1989), subjects were told that they "should respond as rapidly as possible to the first stimulus," and "the experimenter emphasized the importance of making the first response as promptly as possible" (p. 30).

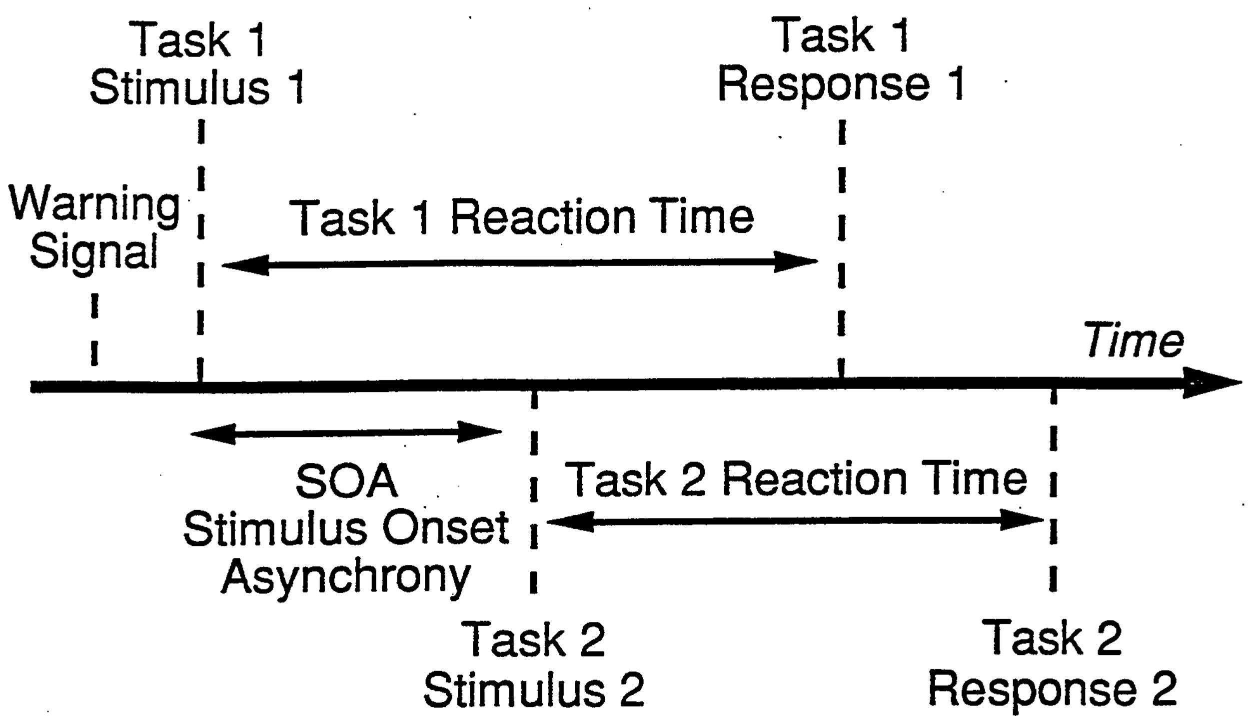

Figure 1. A typical trial in the PRP procedure.

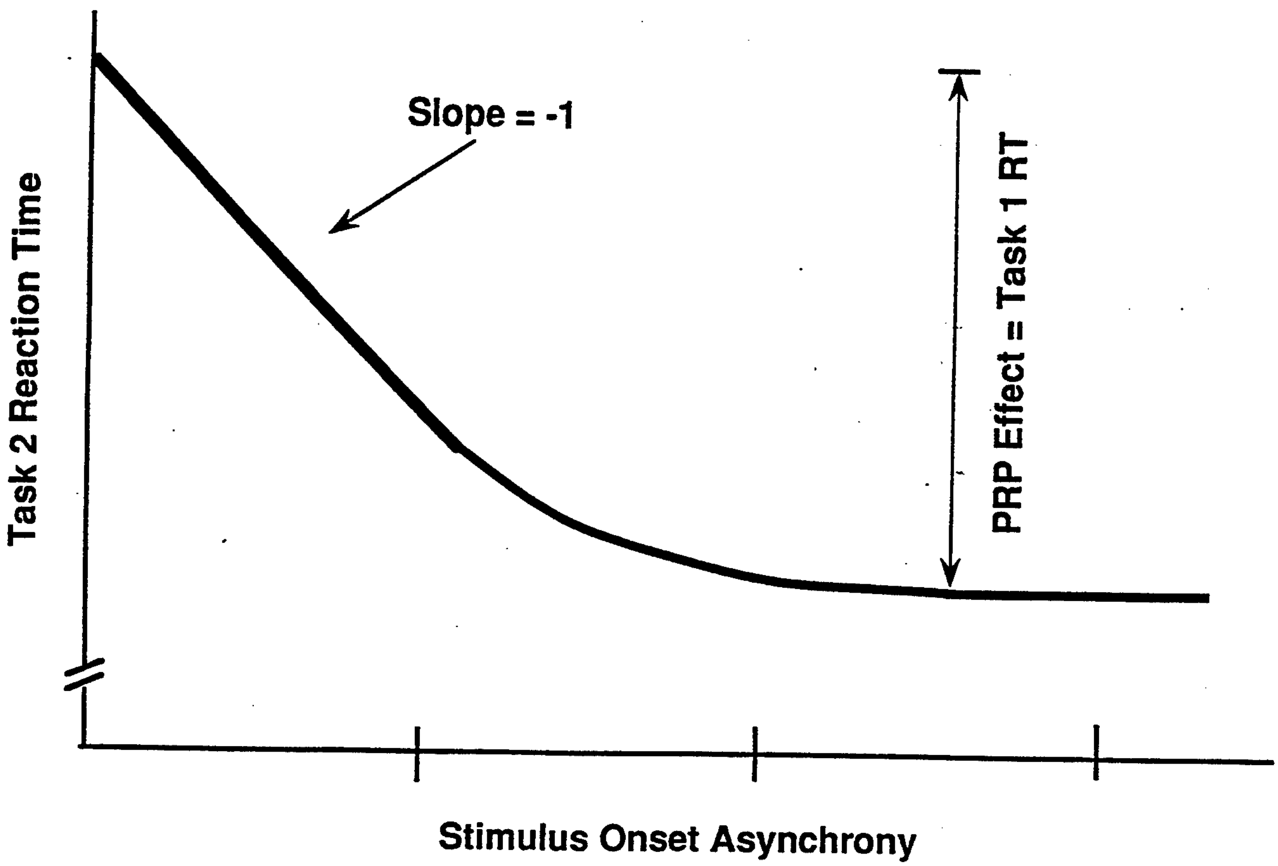

Figure 2. An idealized PRP curve for Task 2 RTs from the PRP procedure.

Evidence for and against the filter theory. To support his assumptions, Broadbent (1958) cited results from experiments on choice RT, dichotic listening, and oral shadowing (e.g., Broadbent, 1952, 1954; Cherry, 1953; Hick, 1952; Hyman, 1953). Nevertheless, soon afterward, other studies yielded significant counter evidence. For example, Moray (1959) and Treisman (1960, 1964) have shown that under some conditions, subjects notice significant amounts of semantic information in putatively unattended auditory messages. Such results, along with other complementary discoveries (e.g., Corteen & Wood, 1972; Gray & Wedderburn, 1960; Lewis, 1970; MacKay, 1973; von Wright, Anderson, & Stenman, 1975), seem antithetical to the filter theory's initial assumptions. Yet phenomena like the PRP effect, which implies strong constraints on multiple-task performance, have persisted (Welford, 1967). Thus, some theorists have looked beyond perceptual (stimulus-identification) processes for bottlenecks elsewhere in the human information-processing system.

Late-selection theory. An influential product of this search is late-selection theory, which has emerged in various related guises (e.g., Deutsch & Deutsch, 1963; Keele, 1973; LaBerge, 1975; Morton, 1969; Norman, 1968; Posner, 1978; Reynolds, 1964; for thorough reviews, see Duncan, 1980a, 1980b; Keele & Neill, 1978; Norman, 1976; Treisman, 1969). The key claim here is that semantic analysis and identification may proceed simultaneously for each of two or more stimuli. On the basis of these processes, stimuli are then supposedly selected for transmission to other functionally subsequent stages, such as conscious attention, memory storage, response selection, and movement preparation or initiation, wherein a single-channel bottleneck might reside.

Response-Selection Bottleneck Model

The version of late-selection theory that most concerns us now is the response-selection bottleneck model (Pashler, 1984, 1990, 1993, 1994a; Smith, 1967; Welford, 1967). Under this model, multiple stimuli may be identified simultaneously and stored in short-term working memory. It is assumed, however, that the process of response selection (i.e., converting symbolic stimulus codes to symbolic response codes; cf. Footnote 1) is only able to accommodate one task at a time. Thus, for concurrent tasks, their respective response-selection stages cannot temporally overlap, and the start of response selection in a secondary task must wait until response selection in an accompanying primary task has finished.

Evidence for a response-selection bottleneck. The response-selection bottleneck model has been used by Smith (1967) and Welford (1968) to account for various results from the PRP procedure. Because this model implies that response selection involves a single-channel mechanism, both the PRP effect and the -1 slope of the PRP curve (Figure 2) are consistent with it. A response-selection bottleneck, coupled with perceptual processes that identify concurrent stimuli in parallel, also explains why the PRP effect may be less than Task 1 RTs.

Moreover, other results have suggested a possible response-selection bottleneck. For example, during several early studies with the PRP procedure, the difficulty of response selection required by Task 1 was varied. Experimenters reasoned that if a response-selection bottleneck exists, then the PRP effect on Task 2 RTs should be directly related to the duration of Task 1 response selection. Accordingly, the PRP effect was found to decrease (Davis, 1959; Fraisse, 1957; Kay & Weiss, 1961; Nickerson, 1965) and even disappear (Borger, 1963; Davis, 1962; Rubinstein, 1964) when subjects did not have to respond overtly to Task 1 stimuli. Null PRP effects also sometimes occur when Task 1 involves "simple" reactions (i.e., only one S-R pair; Adams & Chambers, 1962; Reynolds, 1966). In contrast, as the numerosity of Task 1 S-R pairs increases from one to five, both Task 1 RTs and the PRP effect increase (Karlin & Kestenbaum, 1968; Smith, 1969). Paralleling these results, Broadbent and Gregory (1967) have found that increasing the incompatibility between Task 1 stimuli and responses increases both Task 1 RTs and the PRP effect. This is exactly what the response-selection bottleneck model predicts, given that both S-R numerosity and S-R compatibility probably have their main effects on response selection (Fitts & Seeger, 1953; Hick, 1952; Hyman, 1953; Kornblum, Hasbroucq, & Osman, 1990; Sanders, 1980; Sternberg, 1969).[4]

[4] Alternatively, it might be argued that S-R compatibility or S-R numerosity influence some other stage of processing (e.g., stimulus identification or movement preparation) besides response selection. However, Sternberg (1969) has found

Evidence against a response-selection bottleneck. Nevertheless, some troublesome observations have cast doubt on the response-selection bottleneck model (Kantowitz, 1974; Keele & Neill, 1978). For example, along with varying the number of Task 1 S-R pairs in the PRP procedure, Karlin and Kestenbaum (1968) have also varied the number of Task 2 S-R pairs. In a simple-reaction condition of their study, Task 2 involved a single S-R pair, so subjects had to do little or no response selection on each trial after the Task 2 stimulus was presented. In another choice-reaction condition, Task 2 included two S-R pairs that presumably made the duration of response selection be longer. As a result, the Task 2 RTs at long SOAs were substantially greater under the choice-reaction condition than under the simple-reaction condition. At short SOAs, however, virtually no difference occurred between the mean Task 2 RTs for these two conditions; both simple and choice reactions exhibited a PRP effect, but it was substantially less for the choice reactions, yielding an interaction between SOA and Task 2 response-selection difficulty (Figure 3). As Keele (1973; Keele & Neill, 1978) has argued, this interaction is awkward to explain on the basis of a response-selection bottleneck; instead, it appears that the locus of the bottleneck may be in some later stage of processing.

Figure 4, which embodies *locus-of-slack logic* (Keele, 1973; McCann & Johnston, 1992; Pashler, 1984; Schweickert, 1980), outlines why. Here the processes used to perform Task 1 (top panel), Task 2 in the simple-reaction condition (middle panel), and Task 2 in the choice-reaction condition (bottom panel) have distinctive temporal relations. For Task 1, stimulus identification, response selection, and movement preparation go directly from start to finish. Also, after a short SOA, the stimulus-identification stage of Task 2 proceeds in parallel with Task 1. Then, because of a putative response-selection bottleneck, progress on Task 2 halts temporarily, creating a period of "slack" (Figure 4, dotted intervals) until the Task 1 response is selected. When response selection later resumes in Task 2, it takes more time for choice reactions than for simple reactions, yielding different mean Task 2 RTs (Figure 4, middle versus bottom panels). This difference would be the same regardless of the SOA. Decreasing the SOA would lengthen the slack during Task 2, increasing the Task 2 RTs correspondingly. However, because response selection in Task 2 supposedly begins after the slack for both simple and choice reactions, the effect of response-selection difficulty on Task 2 RTs would not change as the SOA decreases, contrary to what Karlin and Kestenbaum (1968) found.

The response-selection bottleneck model likewise has trouble explaining results reported by Schvaneveldt (1969). He presented visual stimulus digits whose identities and locations varied across trials. There were three types of trial: single-task trials with vocal responses based on digit identities; single-task trials with manual responses based on digit locations; and dual-task trials with vocal plus manual responses. The S-R compatibility also varied systematically. For vocal responses on single-task trials, RTs were longer when subjects named the numerical successors (e.g., "3") of the stimulus digits (e.g., "2") than when they simply named the stimulus digits. Similarly, for manual responses on single-task trials, RTs were longer when subjects pressed finger keys at locations (e.g., right or left) opposite to those of the stimulus digits than when they pressed keys at locations corresponding to those of the digits. On dual-task trials, however, S-R compatibility affected the RTs much less. This reduction is analogous to the interaction that Karlin and Kestenbaum (1968) have found between SOA and S-R numerosity effects on Task 2 RTs. Assuming that S-R compatibility influences response selection, Schvaneveldt's (1969) results suggest that response-selection processes in two concurrent tasks may temporally overlap, contrary to the response-selection bottleneck model (Keele, 1973; Keele & Neill, 1978).

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that S-R compatibility effects are additive with those of factors (e.g., stimulus legibility and response probability) that presumably influence stages earlier and later than response selection. In contrast, S-R compatibility effects interact with those of S-R numerosity (Sternberg, 1969). This pattern suggests that both S-R numerosity and S-R compatibility have some effect during response selection. Indeed, a thorough review of the literature supports the conclusion that response selection is the locus for most, if not all, of both the S-R numerosity and S-R compatibility effects (Sanders, 1980).

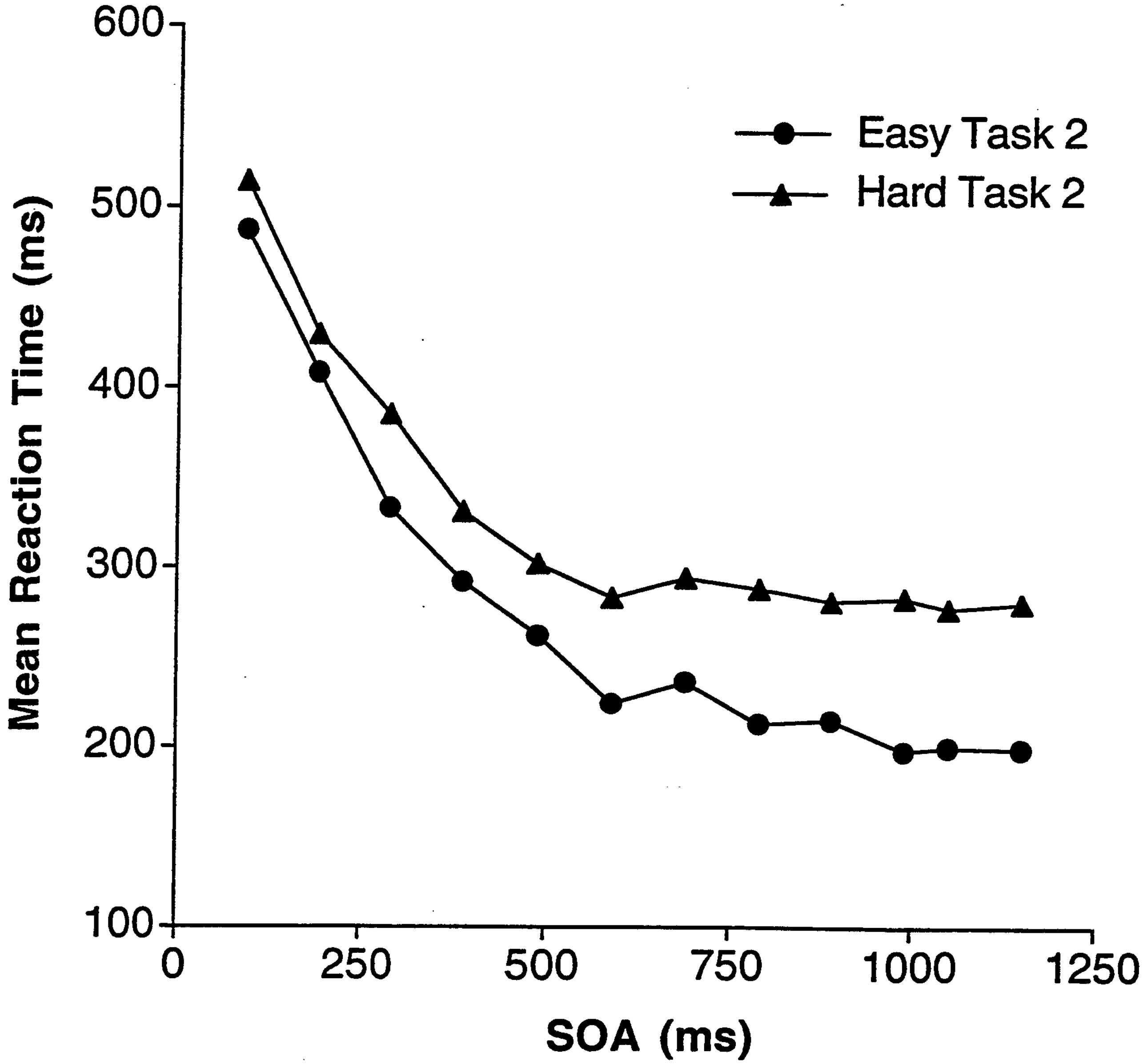

Figure 3. Mean Task 2 RTs from Karlin and Kestenbaum's (1968) study with the PRP procedure. The "easy" and "hard" conditions of Task 2 involve simple reactions (one S-R pair) and choice reactions (two S-R pairs), respectively, manifesting interactions between response-selection difficulty and stimulus-onset asynchrony (SOA). In each case, Task 1 required choice reactions (two S-R pairs).

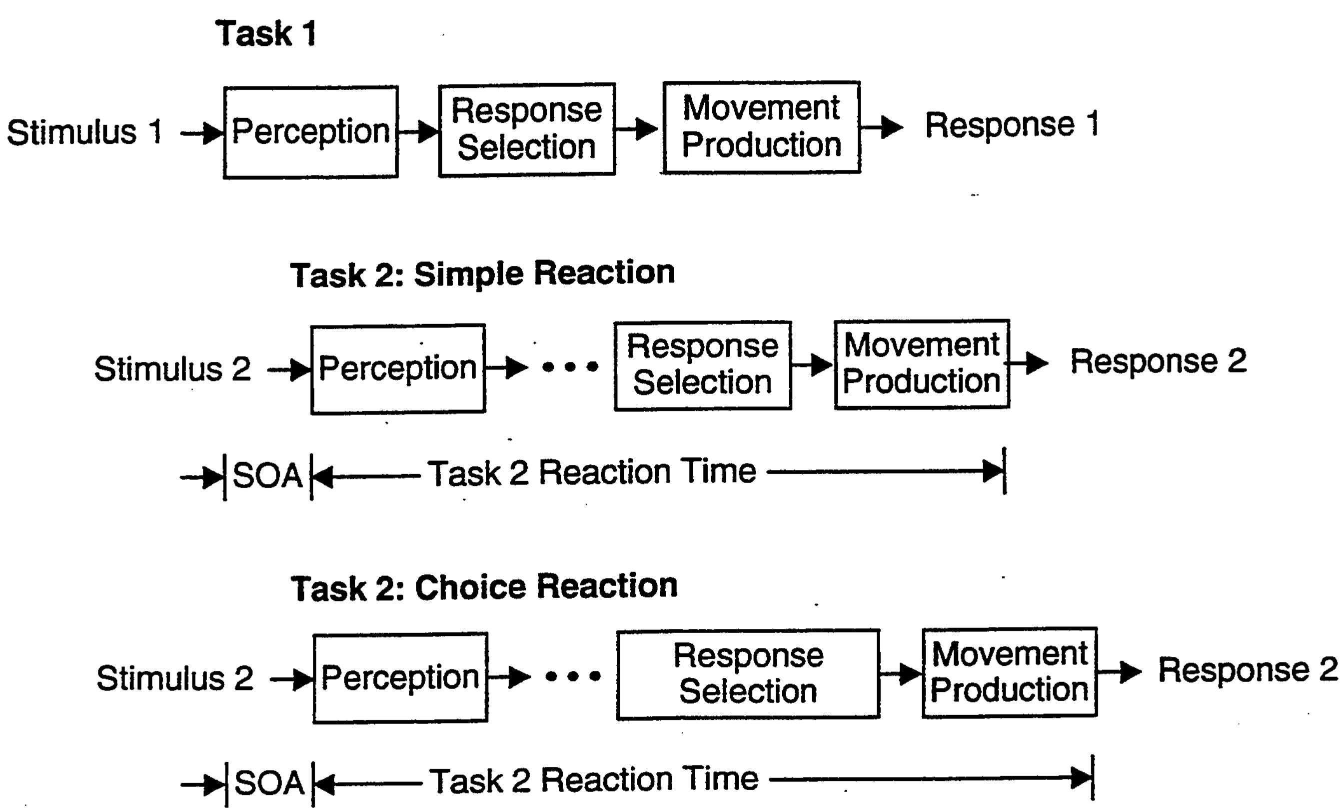

Figure 4. Sequences of processing stages that fail to account for the results of Karlin and Kestenbaum's (1968) PRP study based on locus-of-slack logic and the response-selection bottleneck model. According to this view, response selection in Task 2 takes place after a period of slack (dotted intervals) caused by the response-selection bottleneck, so the SOA and response-selection difficulty (simple vs. choice reactions) should have additive effects on Task 2 RT. For further details, see text.

Movement-Production Bottleneck Model

In light of these results, Keele (1973) looked elsewhere beyond response selection for a single-channel mechanism. His search led him to propose instead a movement-production bottleneck model (also known as the *response-initiation postponement model*; Pashler, 1984). Under it, both stimulus identification and response selection may proceed simultaneously for each of two tasks, but there is a subsequent process that prepares and initiates individual movements successively, and that can accommodate only one task at a time. This latter stage of processing supposedly constitutes a bottleneck that requires a lower-priority task to wait temporarily until a higher-priority task is completed. Closely related ideas have been proposed by several other investigators (e.g., Berlyne; 1960; De Jong, 1993; Herman & Kantowitz, 1970; Kantowitz; 1974, 1977; Logan & Burkell, 1986; Reynolds; 1964).

Evidence for a movement-production bottleneck. As Keele (1973; Keele & Neill, 1978) has argued, the movement-production bottleneck model accounts neatly for results like those of Karlin and Kestenbaum (1968). This account appears in Figure 5, which outlines what should happen during a PRP procedure that involves simple and choice reactions. Here stimulus identification and response selection occur in parallel for Task 1 (top panel), Task 2 with simple reactions (middle panel), and Task 2 with choice reactions (bottom panel). Because of considerations mentioned before, the selection process takes less time for simple reactions than for choice reactions. Also, at a short SOA, some temporal slack precedes movement preparation and initiation in Task 2 (Figure 5, dotted intervals), because of the assumed bottleneck. The slack lets Task 2 response selection be completed for both choice and simple reactions without changing the onset of movement production for Task 2. In turn, this yields equal Task 2 RTs at short SOAs regardless of the reaction type. However, if the SOA were increased, the slack before movement production in Task 2 would diminish, yet the effect of reaction type on response selection for Task 2 would remain. Thus, a difference between Task 2 simple and choice RTs would emerge at long SOAs, yielding an interaction between SOA and reaction type, just as Karlin and Kestenbaum (1968) found. Similarly, this scenario could account for Schvaneveldt's (1969) results on S-R compatibility effects under single-task and dual-task conditions.[5]

Evidence against a movement-production bottleneck. There are, nevertheless, salient pieces of data that cast doubt on the movement-production bottleneck model. For example, with a version of the PRP procedure similar to what Karlin and Kestenbaum (1968) used, Becker (1976) found additive effects of SOA and S-R numerosity on Task 2 RTs; at a very short SOA, the difference between Task 2 RTs involving choice reactions (two S-R pairs) and simple reactions (one S-R pair) was about the same as at longer SOAs. This finding, contrary to the results of Karlin and Kestenbaum (cf. Figure 3), suggests a bottleneck in response selection rather than movement preparation or initiation. Further additivity between the effects of SOA and factors that influence Task 2 response selection, consistent with the response-selection bottleneck model, has been reported by Pashler (1984) and colleagues (e.g., Pashler & Johnston, 1989; McCann & Johnston, 1992; Fagot & Pashler, 1993).

Moreover, some additional results are problematic for both a movement-production bottleneck and other bottleneck models (Gottsdanker, 1980; McLeod, 1978a; Tolkmitt, 1973). Several investigators have found indirect effects of Task 2 factors on Task 1 performance in the PRP procedure. Subjects are sometimes faster at performing a given task alone than at performing it as the first of two tasks (Gottsdanker, Broadbent, & Van Sant, 1963; Herman & Kantowitz, 1970). Task 1 RTs sometimes increase with the number of S-R pairs in Task 2 (Karlin & Kestenbaum, 1968; Smith, 1969). Occasionally, Task 1 RTs increase when SOAs are short rather than long (Gottsdanker & Way, 1966). None of these findings can be explained easily without further embellishing the hypothesized bottleneck mechanisms.

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[5] Extrapolating the inferences drawn from Figures 4 and 5, one may reach a more general statement based on locus-of-slack logic. For any factor that influences a Task 2 stage of processing before the putative locus of the bottleneck, its effects on Task 2 RTs should interact with those of SOA. For any factor that influences the bottleneck stage or other subsequent stages of Task 2, its effects on Task 2 RTs should be additive with those of SOA.

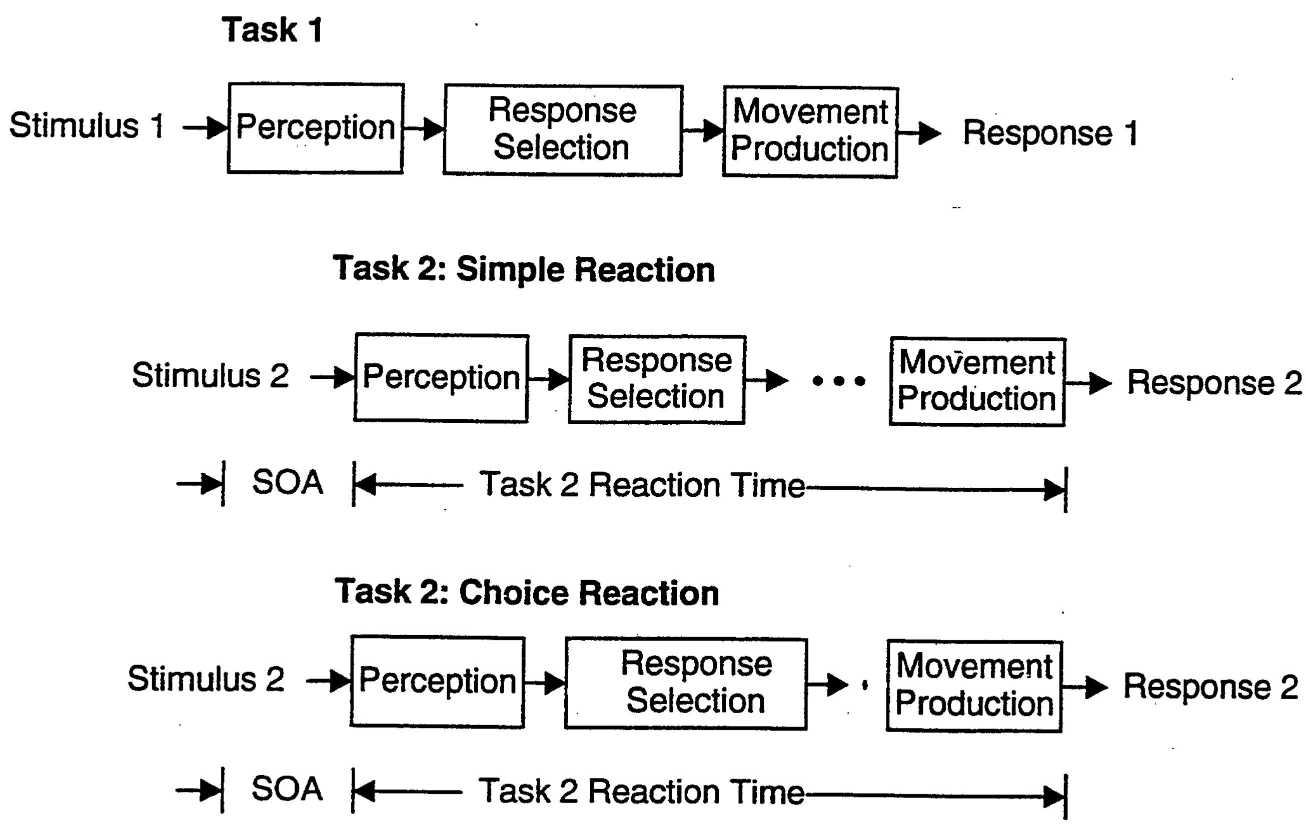

Figure 5. Sequences of processing stages that account for the results of Karlin and Kestenbaum's (1968) PRP study based on locus-of-slack logic and the movement-production bottleneck model. According to this view, response selection in Task 2 takes place before a period of slack (dotted intervals) caused by the movement-production bottleneck, so the SOA and response-selection difficulty (simple vs. choice reactions) should have interactive effects on Task 2 RT. For further details, see text.

Implications of The Bottleneck Models' Successes and Failures

The successes and failures of the competing bottleneck models have significant theoretical implications. Evidence for specific processing stages that deal with only one input at a time and thereby limit multiple-task performance has proven to be rather ambiguous (Allport, 1980a, 1987; Broadbent, 1982; Neumann, 1987). On occasion, some studies have suggested a perceptual bottleneck, while others have suggested either response-selection or movement-production bottlenecks. No general agreement has emerged about where the bottleneck really is.

Given this state of affairs, one could reach several alternative conclusions: (1) the human information-processing system has two or more distinct "hardware" bottlenecks in its component mechanisms (cf. De Jong, 1993, 1994), and their manifestations depend on the prevailing task context; (2) a bottleneck mechanism contributes to multiple-task performance, but the locus at which it operates is strategically programmable and varies from one situation to another, rather than being immutable; (3) there is no bottleneck mechanism per se; (4) performance is mediated instead by a general-purpose central processor with limited capacity that may be allocated continuously and flexibly among competing tasks and stages of processing. For now, the fourth alternative is most relevant, and we consider it next under the rubric of *unitary-resource theory.*

Unitary-Resource Theory

Several versions of unitary-resource theory have been proposed to account for aspects of multiple-task performance not easily explained through the single-channel hypothesis and simple bottleneck models. These accounts differ somewhat from case to case, including terminology such as *operator loading* (Knowles, 1963), *processing capacity* (Moray, 1967), *processing space* (Kerr, 1973), *processing power* (Kiss & Savage, 1977), *processing resources* (Navon & Gopher, 1979; Norman & Bobrow, 1975), *energy pools* (Gopher, 1986), *mental effort* and *attention* (Kahneman, 1973). Despite this plethora of terms, shared among them are certain core ideas; multiple-task performance is mediated by a mental commodity needed for various tasks, and this commodity is quantifiable, divisible, allocatable, and scarce (Wickens, 1991). To illustrate such ideas, we briefly review the unitary-resource theory of Kahneman (1973).

Basic assumptions. Kahneman's (1973, p. 201) theory is based on four assumptions about the nature of available processing capacity, which may be summarized as follows:

"(1) Attention (i.e., capacity) is limited, but the limit is variable from moment to moment. Physiological indices of arousal provide a measure that is correlated to the momentary limit.

(2) The amount of attention (capacity) or effort exerted at any time depends primarily on the demands of current activities. While the investment of attention increases with demands, the increase is typically insufficient to fully compensate for the effects of increased task complexity.

(3) Attention (capacity) is divisible. The allocation of attention is a matter of degree. At high levels of task load (difficulty), however, attention becomes more nearly unitary.

(4) Attention (capacity) is selective, or controllable. It can be allocated to facilitate the processing of selected perceptual units or the execution of selected units of performance. The policy of allocation reflects permanent dispositions and temporary intentions."

Supplementing these assumptions, Kahneman (1973) also noted that multiple-task performance may depend on peripheral and central "structures," such as sensory receptors, memory stores, and motor effectors. His unitary-resource theory therefore admits significant performance decrements that occur when concurrent tasks compete for access to the same structures, yielding *structural interference*. Nevertheless, the theory's main emphasis is on *capacity interference*, a decrement caused by concurrent tasks placing simultaneous demands on an overloaded supply of central processing capacity or mental effort.

Supporting evidence. Considerable empirical evidence supports Kahneman's (1973) unitary-resource theory. Previous data that raised doubts about the existence of a single-channel bottleneck, and that frustrated the search for its specific locus, are congenial to the theory's main assumptions, which do not hypothesize any bottleneck mechanisms per se (e.g., see Gottsdanker, 1980; McLeod, 1978a). If multiple-task performance involves the flexible graded allocation of limited processing capacity to various competing processes, then performance decrements should emerge on a regular basis, but their apparent locus could and would fluctuate in response to differential task demands, as investigators have amply demonstrated through the PRP procedure.

To justify the assumption that processing capacity is somewhat elastic, other evidence may be cited as well. In one intriguing study, Kahneman, Beatty, and Pollack (1967) presented sequences of auditory stimulus digits (e.g., "3816"); after each sequence, subjects vocalized another sequence consisting of the stimulus digits' successors (e.g., "4927"). During presentation of the auditory stimulus digits, the subjects also monitored a sequence of visual letters for a specified target. Their pupil dilation and target-detection accuracy both increased throughout the presentation interval, whereas the vocal digits were produced equally well regardless of serial position. Because pupil dilation presumably manifests arousal and mental effort (cf. Beatty, 1982; Hess & Polt, 1964), these results imply that subjects' capacity to detect the target letter grew over time, while the capacity allocated to the digit-production task remained constant.

More data suggest that processing capacity is indeed divisible and can be flexibly allocated upon demand. For example, Brickner and Gopher (1981) had subjects perform a visual-manual tracking task with one hand while they performed a visual-manual choice-reaction task with the other hand. In one task-emphasis condition, the subjects were told to give 25% priority to the tracking task and 75% priority to the choice-reaction task; in other conditions, the requested percentage priorities were either 0/100, 35/65, 50/50, 65/35, 75/25, or 100/0 for the tracking and choice-reaction tasks, respectively. In particular, the 100/0 condition required subjects to concentrate solely on the tracking task, whereas the 0/100 condition required them to concentrate solely on the choice-reaction task. The changes in task emphasis across conditions helped reveal to what extent subjects could vary the relative amounts of processing capacity devoted to tracking and choice reactions.

Some results of this manipulation appear in Figure 6. Here the speed of choice reactions (responses per second) is plotted versus a measure of normalized tracking accuracy for each task-emphasis condition, yielding a *performance-operating-characteristic* (POC) curve (cf. Navon & Gopher, 1979; Norman & Bobrow; 1975; Sperling & Dosher, 1986). As this curve shows, subjects achieved various intermediate levels of performance; they traded, in gradual fashion, relatively fast choice reactions for relatively accurate tracking. Similar patterns of results, involving other task situations, have been reported by additional investigators (e.g., Gopher, 1993; Gopher, Brickner, & Navon, 1982; Kramer, Wickens, & Donchin, 1985; Navon, Gopher, Chillag, & Spitz, 1984; Sperling & Melchner, 1978; Wickens & Gopher, 1977; Wickens, Kramer, Vanasse, & Donchin, 1983a). This is what one would expect if processing capacity is elastic, continuously divisible, and flexibly allocated.[6]

Problematic phenomena. Yet there are numerous empirical results with which Kahneman's (1973) unitary-resource theory, and other related versions, do not mesh well. Such discrepancies may be best appreciated in the context of the following quote:

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[6] An alternative interpretation of the results in Figure 6 is that subjects switched rapidly back and forth between tasks, devoting their processing capacity to one or the other task in an all-or-none fashion during successive intervals of time (cf. Broadbent, 1982). Perhaps manipulating task emphasis simply affects the relative length of the time interval that each task is given, rather than affecting the proportions of capacity allocated continuously to the two tasks. However, opposing this interpretation, it should also be noted that in Figure 6, the attained performance levels for intermediate task-emphasis conditions (i.e., 25/75, 35/65, 50/50, 65/35, and 75/25) fall above an imaginary diagonal line that connects single-task tracking accuracy (i.e., results from the 100/0 condition) and single-task choice speed (i.e., results from the 0/100 condition). Such dominance suggests that subjects may indeed have performed the two tasks in parallel, rather than alternating serially between them (Sperling & Dosher, 1986).

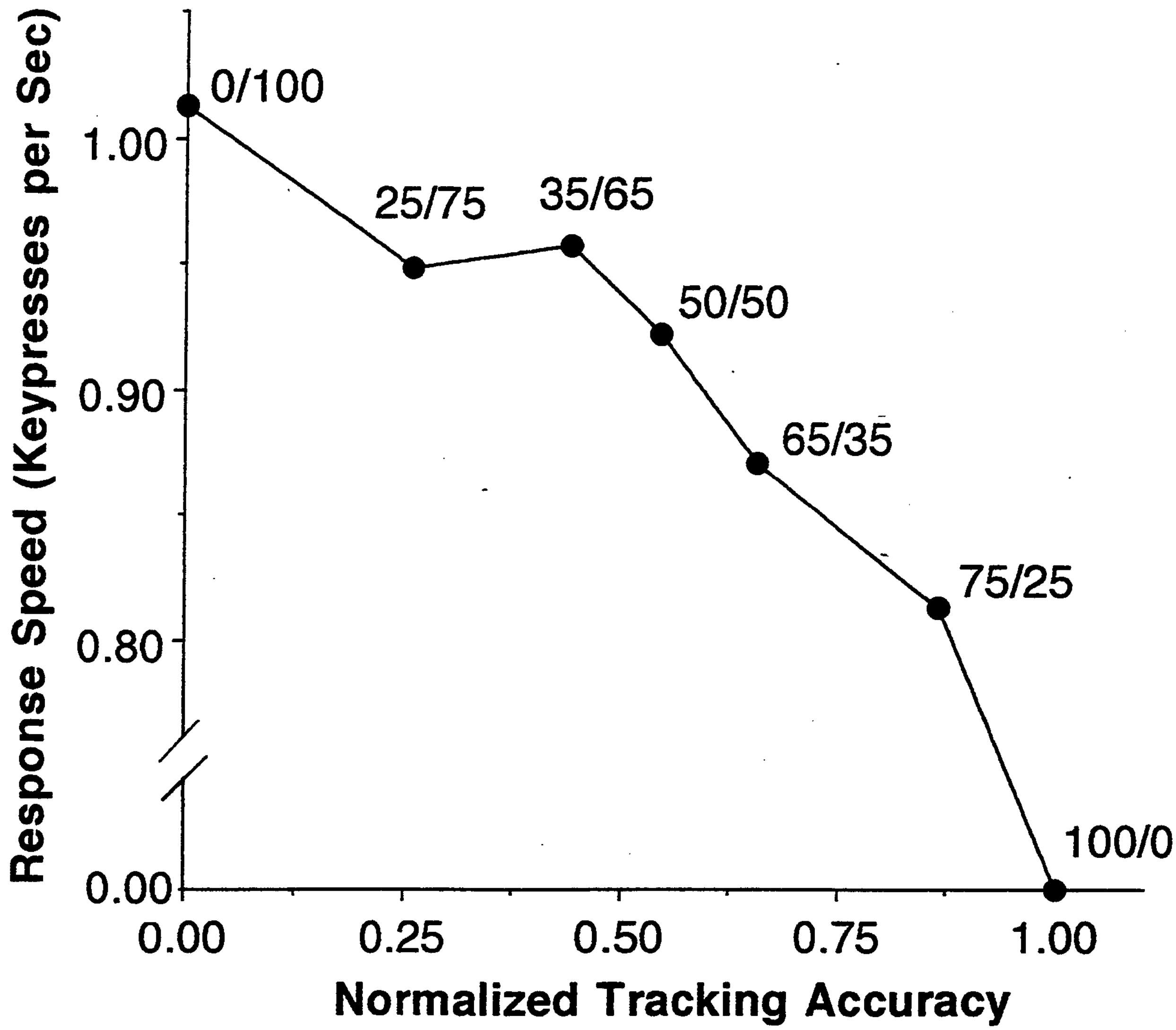

Figure 6. POC curve from a study by Brickner and Gopher (1981) on visual-manual tracking and serial choice reactions (letter typing) in a dual-task procedure. The horizontal axis shows a measure of normalized accuracy (proximity of cursor to target) in the tracking task. The vertical axis shows mean response speed (keypresses per second) in the choice-reaction task. The numerators and denominators of the ratios by the points on the POC curve represent percentages of emphasis given respectively to the tracking and choice-reaction tasks in various conditions. For example, in the 25/75 condition, the tracking task received 25% emphasis, and the choice-reaction task received 75% emphasis. The 0/100 and 100/0 conditions corresponded respectively to performing the choice-reaction or tracking task alone.

"A theory which identifies attention with effort and limited capacity entails two predictions concerning interference between concurrent activities: (1) interference will arise even when two activities do not share any mechanisms of either perception or response; (2) the extent of interference will depend in part on the load which each of the activities imposes, i.e., on the demands of competing activities for effort or attention" (Kahneman, 1973, pp. 178-179).

Opposing the latter predictions, Wickens (1980, 1984, 1991) has catalogued four problematic phenomena: difficulty insensitivity, structural-alteration effects, difficulty-structure uncoupling, and perfect time-sharing. Together, these phenomena suggest that structural interference (e.g., competition among tasks for access to limited peripheral sensory and motor mechanisms), rather than central capacity interference, may be the primary source of performance decrements in many, perhaps even all, multiple-task situations.

Difficulty insensitivity occurs when varying the nominal difficulty of a primary task has little or no effect on subjects' performance of a concurrent secondary task. For example, North (1977) had subjects perform a primary visual-manual choice-reaction task along with either a secondary digit-cancellation task or a secondary visual-manual tracking task. The primary task's difficulty was varied by manipulating the complexity of decisions that subjects made there. When performed alone, the primary task yielded increasing RTs and error rates as its difficulty increased. Performance on the secondary digit-cancellation task also became worse as the primary-task difficulty increased. Thus, the processing capacity required by the primary task presumably increased with its difficulty. However, manipulation of the primary task's difficulty did not significantly affect performance on the secondary tracking task. In addition, other researchers have reported several cases of such difficulty insensitivity (e.g., Isreal, Chesney, Wickens, & Donchin, 1980; Kantowitz & Knight, 1976; McLeod, 1977; Wickens & Kessel, 1979), contrary to predictions made by Kahneman's (1973) unitary-resource theory.

Structural-alteration effects occur when two circumstances jointly prevail: (1) primary-task interference with a secondary task is dramatically reduced by changing which structural components are needed to perform the primary task; (2) this change does not decrease the primary task's difficulty. For example, McLeod (1977, Exp. 1) had subjects perform a secondary visual-manual tracking task along with a primary choice-reaction task. The primary task required either manual or vocal responses to auditory tones. Both types of primary-task response were about equally difficult to make. However, the primary task interfered much less with the secondary visual-manual tracking task when the primary-task responses were vocal rather than manual. More generally, structural-alteration effects have been obtained through variations of not only primary-task response modalities (Harris, Owens, & North, 1978; McLeod, 1978b; Wickens, 1980; Wickens, Sandry, &Vidulich, 1983), but also stimulus modalities (Martin, 1980; Treisman & Davies, 1973; Wickens et al., 1983), and mental imagery codes (Brooks, 1968; Friedman, Polson, Gaskill, & Dafoe, 1982; McFarland & Ashton, 1978; Wickens & Sandry, 1982; Wickens et al., 1983). Such results suggest that decrements observed in multiple-task performance may stem not from capacity interference per se, but rather from stimulus confusions, response competition, and other sources of structural interference.

Difficulty-structure uncoupling occurs when structural-alteration effects reduce the interference between primary and secondary tasks at the same time as the primary-task difficulty actually increases (Wickens, 1984). An illustrative case of this counter-intuitive pattern has been found by Wickens (1976). His subjects performed a secondary visual-manual tracking task together with either a primary auditory signal-detection task or manual force-generation task. According to unanimous subjective reports, the force-generation task was easier than the signal-detection task. Nevertheless, the force-generation task interfered more with the tracking task. As before, this casts doubt on the limited-capacity and capacity-demand assumptions, which predict more interference between signal detection and manual tracking, given the greater difficulty of the detection task.

Structural-alteration effects and difficulty-structure uncoupling can even lead to *perfect time-sharing* (Wickens, 1984), which occurs when neither of two individually demanding tasks interferes with the other during dual-task performance. For example, Allport, Antonis, and Reynolds (1972) showed that subjects could simultaneously shadow spoken messages and play piano music from written scores with essentially no performance decrements compared to single-task levels. Similarly, using the PRP procedure, Greenwald and Shulman (1973) virtually eliminated the PRP effect when Task 1 and Task 2 both involved ideomotor-compatible S-R mappings. Shaffer (1975) found no marked performance decrements when skilled typists simultaneously typed written text and orally shadowed spoken messages. Hirst, Spelke, Reaves, Caharack, and Neisser (1980) found that after some practice, subjects successfully comprehended written stories while they manually transcribed auditory stimulus words. Given that most, if not all, of the tasks involved here were reasonably demanding, these repeated occurrences of perfect time-sharing seem especially antithetical to the limited-capacity assumption of unitary-resource theory.

Augmentation of unitary-resource theory. Confronted by the preceding antitheses, some investigators have tried to augment unitary-resource theory with additional conceptual refinements and ancillary mechanisms, while retaining the assumption of limited central-processing capacity. For example, Norman and Bobrow (1975) introduced a distinction between resource-limited and data-limited processes, which may help the theory account for phenomena like difficulty insensitivity.[7] However, such accounts have not satisfied the theory's adamant critics (e.g., Allport, 1980a, 1987, 1993; Neumann, 1987). In their opinion, continued adherence to an assumption of limited central-processing capacity is counter-productive and distracts theorists from analyzing other more crucial determinants of multiple-task performance, such as the relationships among specific central and peripheral processing structures. This concern has inspired the development of multiple-resource theory, which abandons a narrow limited-capacity assumption and reconceptualizes the nature of available "resources."

Multiple-Resource Theory

There are several versions of multiple-resource theory. For now, we focus on one popularized by Navon and Gopher (1979). Other related cases may be found elsewhere (e.g., Allport et al., 1972; Gopher & Sanders, 1984; Greenwald & Shulman, 1973; Kantowitz & Knight, 1976; McLeod, 1977; McLeod & Posner, 1984; Wickens, 1980, 1984).

Basic assumptions. Under Navon and Gopher's (1979) multiple-resource theory, various disjoint sets of processing resources are used in combination for performing individual tasks. Each set of resources is assumed to have its own separate divisible source of capacity. If two or more tasks require the same set of resources, then the capacity available to them is supposedly allocated in a flexible graded fashion, depending on current task requirements. Consequently, the tasks may all be performed at the same time, albeit with a reduced rate of progress on each one relative to single-task conditions. In contrast, if each of two or more tasks requires an entirely different set of resources, then progress on them may proceed simultaneously without any interference, because there is no need to share the same capacity among tasks.

Taxonomy of resources. Further elaborating these assumptions, Wickens (1984) suggested a three-dimensional taxonomy of resources based on *stages*, *codes*, and *modalities* of processing (cf. Norman & Bobrow, 1975). His first dimension includes a perceptual/cognitive stage and a response stage. Each of these stages is assumed to have its own divisible source of capacity. Thus, if two tasks (e.g., visual letter matching and word recognition) both require perceptual/cognitive processing, then they would presumably interfere with each other, whereas two tasks (e.g., visual letter matching and manual force production) that respectively require perceptual/cognitive and response processing would interfere relatively little with each other.

The second dimension of Wickens's (1984) taxonomy distinguishes between spatial and verbal codes. Stages of processing that use the same type of code are assumed to share resources and capacity. As a result, interference would presumably occur between two tasks when they both require verbal coding (e.g., serial digit rehearsal and sentence comprehension) or both require spatial coding (e.g., map reading and maintenance of a visual image). In contrast, two tasks that require different types of code would not suffer interference when performed together (cf. Brooks, 1968).

[7] Proponents of simple bottleneck models have also sought to reconcile their views with phenomena like difficulty insensitivity. Specifically, Broadbent (1982) tried to account for structural-alteration effects, difficulty-structure uncoupling, and perfect time-sharing in terms of rapid serial interleaving of various processing stages.

Third, there is a dimension that distinguishes various sensory and motor modalities. Here, vision and audition are assumed to be separate, each having its own dedicated set of resources and capacity. Also, the manual and vocal modalities are separate. Thus, two tasks would presumably interfere much more with each other if they both involve the same sensory modality (e.g., vision) and/or same motor modality (e.g., manual) than if they involve entirely different modalities (e.g., visual/manual combined with auditory/vocal).

Virtues of the theory. On the basis of Wickens's (1984) taxonomy, the multiple-resource theory -- with its diverse sets of structural resources and reservoirs of processing capacity -- broadly generalizes the unitary-resource theory. This generalization can account not only for specific cases of between-task interference but also for the plethora of problematic phenomena by which unitary-resource theory has been bedeviled. If two or more tasks require some of the same resources, then changing the task configuration so that it instead entails disjoint sets of resources should yield large structural-alteration effects and difficulty-structure uncoupling. Also, difficulty insensitivity and perfect time-sharing could naturally emerge (cf. Wickens, 1984). The theory's assumed resource-specific capacities likewise explain how and why people might respond gracefully to changing task emphases in situations where between-task interference does occur (Navon & Gopher, 1979).

In addition, some aspects of neuroanatomy and neurophysiology accord well with multiple-resource theory. For example, Kinsbourne and Hicks (1978) noted that concurrent tasks may be easier when one of them relies on the brain's right hemisphere whereas another relies on the left hemisphere. This easy concurrency could stem from the two hemispheres providing distinct resources that mediate the use of spatial and verbal codes, respectively (cf. Friedman & Polson, 1981; Friedman et al.; 1982; Hellige, Cox, & Litvac, 1979; Kinsbourne & Cook, 1971; Liederman, 1986). Similarly, Pribram and McGuinness (1975) suggested that processing capacity may have two distinct sources: "arousal" from the brain's reticular-activating system (RAS), and "activation" from the limbic system and basal ganglia. Following this suggestion, Sanders (1983), and Gopher and Sanders (1984) related RAS arousal to the perceptual/cognitive stage of processing, and limbic-system activation to the response stage. These putative relations are consistent with selective effects of psychoactive drugs (e.g., barbiturates and amphetimine) on human performance (Frowein, 1981).

Backlash of Theoretical Criticism

Nevertheless, despite the virtues of multiple-resource theory, a strong backlash of criticism has been directed against it. Several critics have questioned the theory's conceptual foundations (e.g., Hirst & Kalmar, 1987; Navon, 1984, 1985; Neumann, 1987). One of their concerns is that at present, the concept of multiple resources lacks sufficient principled constraints. In the absence of such constraints, there is a seductive temptation to hypothesize new sets of resources whenever additional problematic data are collected. This could ultimately lead to an amorphous potpourri of theoretical concepts without parsimony or predictive power.

Concomitantly, empirical reservations about radical versions of multiple-resource theory have grown steadily as well. Various studies have revealed decrements in stimulus detection, recognition, identification, and classification when multiple targets are presented simultaneously (for a review, see Duncan, 1980a). These decrements apparently occur even when stimuli are presented through different sensory modalities (Long, 1975) and do not require immediate overt responses (Duncan, 1980b). This suggests that it is perhaps premature to reject prior hypotheses about perceptual bottlenecks and central single-channel decision mechanisms.

Reinforcing the latter reservations, Pashler (1984, 1989, 1990, 1993, 1994a, 1994b) and some other investigators have continued to champion the traditional response-selection bottleneck model. Their studies with the PRP procedure have revealed PRP effects on Task 2 RTs even when Task 1 requires vocal responses to auditory stimuli and Task 2 requires manual responses to visual stimuli (McCann & Johnston, 1992; Pashler, 1990; Pashler & Johnston, 1989). Task 2 RTs may manifest additive effects of SOA and various Task 2 factors that presumably influence response selection, including decision type (positive versus negative; Pashler, 1984), S-R numerosity (Becker, 1976; Van Selst & Jolicoeur, 1993), S-R compatibility (McCann & Johnston, 1992), S-R repetition (Pashler & Johnston, 1989), and S-R conflict (Stroop interference; Fagot & Pashler, 1993). Such additivity can occur even when subjects respond to two perceptual features of the same stimulus (Fagot & Pashler, 1993). For reasons mentioned earlier (Figure 4), these findings seem to suggest a bottleneck in response selection, rather than flexible allocation of capacity to concurrent selection processes. Further complicating the theoretical picture, hybrid models with a combination of both response-selection and movement-production bottlenecks have been proposed (De Jong, 1993).

Theoretical Diagnoses and Prescriptions

From our review of past literature, one might justifiably diagnose research on multiple-task performance as being in a state of substantial disagreement and confusion. Numerous qualitative hypotheses, models, and theories have been proposed to characterize how people perform concurrent tasks. They have been tested through a variety of experimental procedures whose combined results now constitute an impressively large data base. However, given the comings and goings of single-channel hypotheses, bottleneck models, and resource theories, skeptics have worried about whether this research has done much more than "chase its own tail" (Allport, 1980a, 1987; Newell, 1973a).

What can be done now to help resolve the persisting controversies and promote cumulative scientific progress? Fortunately, in answer to this question, concerned observers have offered at least some promising prescriptions.

Development of Computational Models

One essential next step has been prescribed by Newell (1973a). With respect to computational modeling, he gave cognitive scientists an explicit directive:

> "... construct complete processing models rather than the partial ones we now do.... (These models should be) embodied in a simulation, actually carry out the experimental task, ... (and have) detailed control structure coupled with equally detailed assumptions about memory and elementary control processes ... in the same fashion as discovering a program in a given programming language to perform a specified task. ...the attempts in some papers to move toward a process model by giving a flow diagram ... seem ... not to be tight enough" (Newell, 1973a, pp. 300-302).

Following Newell's sentiments, other researchers have also urged the development of computational models for human multiple-task performance. As Allport and Broadbent have put it:

> "What is urgently needed is ... a computational theory, in the sense outlined by Marr (1982), of the many different functions of attentional selectivity and control ... taking seriously the idea that attentional functions are of many different kinds, serving a great range of different computational purposes" (Allport, 1993, pp. 205-206).

> "We need computational theories of interaction between stages. As the number of theoretical entities increases in each area, it becomes increasingly hard to see the implications of combining them. Only computational systems can do this, and they will have the merit of stopping the laxness of definition noted by Allport" (Broadbent, 1993, p. 876).

What form should the requisite computational models take? Again, we may look to Newell (1973b) and other like-minded investigators (e.g., Allport, 1980b; Anderson, 1976, 1983, 1993; Hunt & Lansman, 1986; Laird, Newell, & Rosenbloom, 1987; Logan, 1985; Seifert & Shafto, in press; Townsend, 1986) for a promising answer. According to them, *production systems* -- sets of condition-action rules that manipulate the contents of a working-memory store and regulate input/output activities -- provide a powerful descriptive computational-modeling tool. Moreover, with respect to multiple-task performance in particular, Broadbent (1993, p. 876) has remarked that production systems are an especially useful formalism because they enable flexible shifting of task goals, context-dependent application of condition-action rules, and other operations for coordination of concurrent tasks.

Specification of Information-Processing Architecture

As part of an endeavor to develop complete precise computational models, a second essential step entails specifying a general integrated information-processing architecture, which provides a stable structural framework with a fixed set of component modules for designing particular computational models in a variety of task situations. Across situations, the components of the architecture should stay the same, embodying universal "hardware" aspects of human information processing that govern perception, memory, cognition, and action. On the basis of this constraint, a theorist can better understand, describe, and predict how other strategic "programmable" aspects of performance change systematically from one context to the next.

The importance of having well-specified information-processing architectures has been emphasized repeatedly by Newell (1973a, 1990) and other investigators (e.g., Anderson, 1976, 1983, 1993; Atkinson & Shiffrin, 1968; Card, Moran, & Newell, 1983; Laird et al., 1987):

> "Our task in psychology is first to discover the invariant structure of processing mechanisms.... Without such a framework within which to work, the generation ... of new explanations for old phenomena will go on *ad nauseum*" (Newell, 1973a, pp. 293, 296).

Practicing what he preached, Newell (1990; Laird et al., 1987) implemented one illustrative architecture, the SOAR system, through which computational models for learning, memory, and reasoning may be built. Similarly, Anderson (1976, 1983, 1993) has modeled various aspects of learning, memory, and cognition with his ACT, ACT*, and ACT-R architectures. Although Card et al. (1983) did not develop many executable computational models, they have shown how an integrated system architecture can likewise help elucidate human-computer interaction. In light of these precedents, it seems likely that specifying an integrated architecture for human multiple-task performance could yield substantial benefits as well.

Incorporation of Perceptual-Motor Processors

As part of the requisite architecture, detailed perceptual-motor processors must be included. Because people have limited numbers of sensors and effectors (e.g., two eyes, two ears, two hands, and one mouth), representing the constraints imposed by them is essential to understanding multiple-task performance (Allport, 1980a, 1987; Neisser, 1976; Neumann, 1987). Only through such representation may one determine how people cope with their physical limitations in the face of competing task demands and strategic goals:

> "The constraints of the human body set upper limits on the degrees of freedom of our physical action. A limb cannot be in two positions at once. We cannot shift our gaze simultaneously to right and left, nor vocalize two different syllables at the same time.... Certainly, many of the phenomena attributed hitherto to 'attentional' or 'general-capacity' limitations can be seen to depend on situations in which separate inputs compete for or share control of the same category of action.... It may be that, until we have a better description of what is being done by at least some of the sub-systems, questions about the overall architecture will just be premature" (Allport, 1980a, pp. 144, 145, 148).

Analysis of Executive Processes

There is also a third essential step to be taken toward a better understanding of human multiple-task performance. It entails analyzing the executive processes and task strategies that people use in various situations. Such analyses are necessary for several reasons:

"the same human subject can adopt many radically different methods for the same basic task, depending on goals, background knowledge, and minor details of payoff structure.... To predict a subject you must know: (1) his goals; and (2) the task environment.... Until one has a model of the control processes ... we will not be able to bring the problem of specifying subjects' methods under control" (Newell, 1973a; pp. 293, 299, 301).

"If we do *not* postulate some agent who selects and uses ... stored information, we must think of every thought and every response as just the momentary resultant of an interacting system, governed essentially by laissez-faire economics. Indeed, the notions of 'habit strength' and 'response competition' used by the behaviorists are based exactly on this model. However, it seems strained and uncomfortable where selective thought and action are involved .... Today, the stored-program computer has provided us with an alternative possibility, in the form of the *executive routine*. This is a concept which may be of considerable use to psychology.... Common practice is to make all subroutines end by transferring control to the executive, which then decides what to do next in each case. ...the executive may take only a small fraction of the computing time and space allotted to the program as a whole, and it need not contain any very sophisticated processes" (Neisser , 1967, p. 293-296).

Pursuing these considerations further, some theorists have begun to describe the functions of executive processes more fully in human multiple-task performance (e.g., Baddeley, 1986; De Jong, 1995; Duncan, 1986; Logan, 1985; McLeod, 1977; Norman & Shallice, 1986; Shallice, 1972; Shiffrin & Schneider, 1977). Although such descriptions have not yet yielded detailed comprehensive computational models, they appear quite promising. An especially relevant technique that may help us further is GOMS methodology, which defines control structures in terms of four distinct entities: *goals*, *operators*, *methods*, and *selection rules* (Card et al., 1983; Gray, John, & Atwood, 1993; John, 1988, 1990; John, Vera, & Newell, 1994; Kieras, 1988; Kieras & Polson, 1985; Polson & Kieras, 1985). Also potentially relevant here is *critical-path analysis* (Gray et al., 1993; John, 1988, 1990; Schweickert & Boggs, 1984), a technique for representing temporal relations among serial and parallel component processes in interactive processing systems.

Omission of Limited-Capacity Assumption

To develop instructive computational models of multiple-task performance, a fourth step is perhaps essential too. The assumption of limited general-purpose processing capacity -- which pervaded the single-channel hypothesis, bottleneck models, and unitary-resource theory -- should be omitted at least for the moment. There are many reasons why (Allport, 1980a; 1987; 1989; 1993; Neisser, 1976; Neumann, 1987). For example, as Allport (1980a, pp. 117-118, 121) has warned, assuming on an a priori basis that processing capacity is limited may yield a singularly unproductive research program:

"Obviously there is a problem of how we know when we are dealing with competition for a single resource.... Once one accepts the idea of general-purpose processing capacity as a working hypothesis, it becomes temptingly easy to assume, without further ado, that almost any instance of dual-task interference is a result of competition for this same general resource, for 'attention'.... The theory, at least in its application, appears to be entirely circular.... The result is a strategy of research that can do nothing but chase its own tail.... This has been a singularly unproductive heuristic for the discovery of the architectural constraints on concurrent psychological processes.... It merely soothes away curiosity by the appearance of having provided an explanation, even before the data have been obtained."

Omission of the limited-capacity assumption may also be justified from neurophysiological considerations (Neisser, 1976; Neumann, 1987; Rumelhart & McClelland, 1986). For example, inspired by connectionist and neural-network modelers, Neumann (1987, p. 362) has pointed out:

> "(There is no) physiologically established limit on the information that can be picked up at the same time. Neither are there obvious neurophysiological grounds for the assumption that dual-task performance is limited by the hardware properties of the brain. There is an immense amount of parallel computation going on simultaneously in the awake brain (see Anderson & Hinton, 1981; Creutzfeldt, 1983); and there are many subsystems that integrate information from different sources without an indication of limited capacity."

Theoretical Framework

Guided by the preceding diagnoses and prescriptions, the remainder of this article introduces a comprehensive theoretical framework for developing precise computational models and applying them to characterize human multiple-task performance under a variety of conditions. In what follows, we next outline the heuristic principles embodied by our framework, and we describe two of its major facets: a production-system formalism, and an integrated information-processing architecture.

Heuristic Principles

Our theoretical framework embodies five general heuristic principles:

Integrated information-processing architecture. First, as indicated already, we develop our models within an integrated information-processing architecture. This architecture is intended to faithfully incorporate known characteristics of human information processing and performance. It extends work by previous researchers who have strived toward unified theories of cognition and action (e.g., Anderson, 1976, 1983, 1993; Card et al., 1983; Laird et al., 1987; Newell, 1990).

Production-system formalism. Second, again like these and other previous researchers (e.g., Hunt & Lansman, 1986; Townsend, 1986), we adopt a production-system formalism for creating the simulation programs that instantiate our computational models. This lets us specify exactly what procedural knowledge is used to perform particular tasks separately and in various combinations.

Omission of limited processing-capacity assumption. Third, our models impose no obligatory upper bound on the number of tasks for which information may be processed centrally at the same rate as in single-task situations. In this sense, which is elaborated more fully later, we omit an assumption of limited central-processing capacity, following prescriptions offered by some critics of the single-channel hypothesis, bottleneck models, and unitary-resource theory (e.g., Allport, 1980a, 1987; Neisser, 1976; Neumann, 1987).

Emphasis on task strategies and executive processes. Fourth, rather than using the limited processing-capacity assumption to explain observed decrements in multiple-task performance, we instead attribute them as much as possible to flexible strategies that people adopt to satisfy particular task instructions. Consequently, our models emphasize the role played by supervisory executive processes, as Neisser (1967) and others (e.g., Baddeley, 1986; Duncan, 1986; Logan, 1985; McLeod, 1977; Norman & Shallice, 1986; Shallice, 1972) have advocated.

Detailed treatment of perceptual-motor constraints. Fifth, we take detailed account of perceptual-motor constraints on multiple-task performance. Our information-processing architecture includes explicit assumptions about the properties of perceptual and motor processes, which honor available empirical data (e.g., Atkinson et al., 1988; Meyer & Kornblum, 1993).

Production-System Formalism

In accord with these heuristic principles, the present theoretical framework relies on a production-system formalism called the *Parsimonius Production System* (PPS; Covrigaru & Kieras, 1987). Like other production systems (e.g., Anderson, 1976, 1983, 1993; Hunt & Lansman, 1986; Laird et al., 1987; Newell, 1973b, 1980, 1990), PPS has a working memory, production rules expressed as condition-action (if-then) statements, and a rule interpreter. The components of PPS are tailored to promote computational simplicity, clarity, flexibility, and power. Previous research has demonstrated PPS's utility for modeling a variety of cognitive activities, including text comprehension (Bovair & Kieras, 1991), procedural learning (Kieras & Bovair, 1986), and human-computer interaction (Bovair, Kieras, & Polson, 1990; Kieras & Polson, 1985; Polson & Kieras, 1985).

PPS control structure. Of special interest for modeling multiple-task performance, PPS uses no complex conflict-resolution criteria or spreading-activation mechanisms to control which production rules are applied at a particular moment in time (cf. Anderson, 1976, 1983, 1993; Hunt & Lansman, 1986; McDermott & Forgy, 1978). Instead, the application of rules in PPS depends solely on the rules' conditions and the contents of working memory. Whenever the condition of any PPS rule is satisfied by the current contents of working memory, all of its actions are executed immediately, regardless of the status of other rules. To preclude simultaneous conflicting actions, the conditions of the rules must be defined such that two or more rules are never applied at the same time if their actions conflict. As illustrated later, this restriction may be achieved in part by having the rules' conditions include explicit steps, which help guide the sequence of rule applications.

Parallelism in PPS. Another important feature of PPS is that it enables substantial parallel processing. With the PPS production-rule interpreter, multiple production rules are tested at the same time, and all of their actions may be executed simultaneously whenever the conditions associated with them are mutually satisfied by the contents of working memory. This facilitates our construction of computational models that omit central processing bottlenecks.

Architecture for Computational Modeling

A second facet of the present theoretical framework is an integrated information-processing architecture within which models of single-task and multiple-task performance may be developed. For reasons that will become more apparent later, we call our architecture *EPIC*, an acronym for *Executive-Process Interactive Control.* Figure 7 outlines EPIC's principal components. They consist of several complementary memory stores and processing units that interact with each other heterarchically. The processing units are implemented as modules of instructions written in LISP, a programming language for symbolic computation in artificial intelligence.

Memory stores. EPIC has three functionally distinct memory stores: declarative long-term memory, procedural memory, and working memory. *Declarative long-term memory* contains knowledge expressed as propositions, which embody the gist of verbal descriptions about when, where, why, and how to perform particular tasks. *Procedural memory* contains PPS production rules that instantiate procedural knowledge for actually performing the tasks. These rules may be derived through a process of "proceduralization" that converts declarative propositional knowledge to a directly executable form (Anderson, 1982; Bovair & Kieras, 1991; Kieras & Bovair, 1986). *Working memory* contains symbolic control information needed for testing and applying the production rules stored in procedural memory. Symbolic representations of stimulus inputs and response outputs are also stored in EPIC's working memory for use by the system's production rules.[8]

Processing units. Among EPIC's processing units are visual, auditory, and tactile *perceptual processors* that receive inputs from simulated *physical sensors* (e.g., virtual eyes and ears). Each perceptual processor sends outputs to working memory, which is used by a *cognitive processor* to perform various tasks. The cognitive processor relies on the PPS production-rule interpreter, which tests the conditions and executes the actions of the production rules in procedural memory. Through this interpreter, the cognitive processor selects symbolic responses and sends them to vocal and manual *motor processors*, which prepare and initiate movements by simulated *physical effectors.* In addition, there is an ocular motor processor for moving EPIC's eyes, whose spatial position determines what inputs may enter the visual perceptual processor. With its various components, EPIC has capabilities to emulate a broad range of human perceptual-motor and cognitive skills.

[8] For present purposes, we depict EPIC's working memory as a single store that contains various types of functionally distinct information. In other contexts, however, it would be more appropriate to treat working memory as having a number of separate partitions, in each of which the form, amount, and duration of the contents differ from those of the other partitions (Kieras & Meyer, 1996).

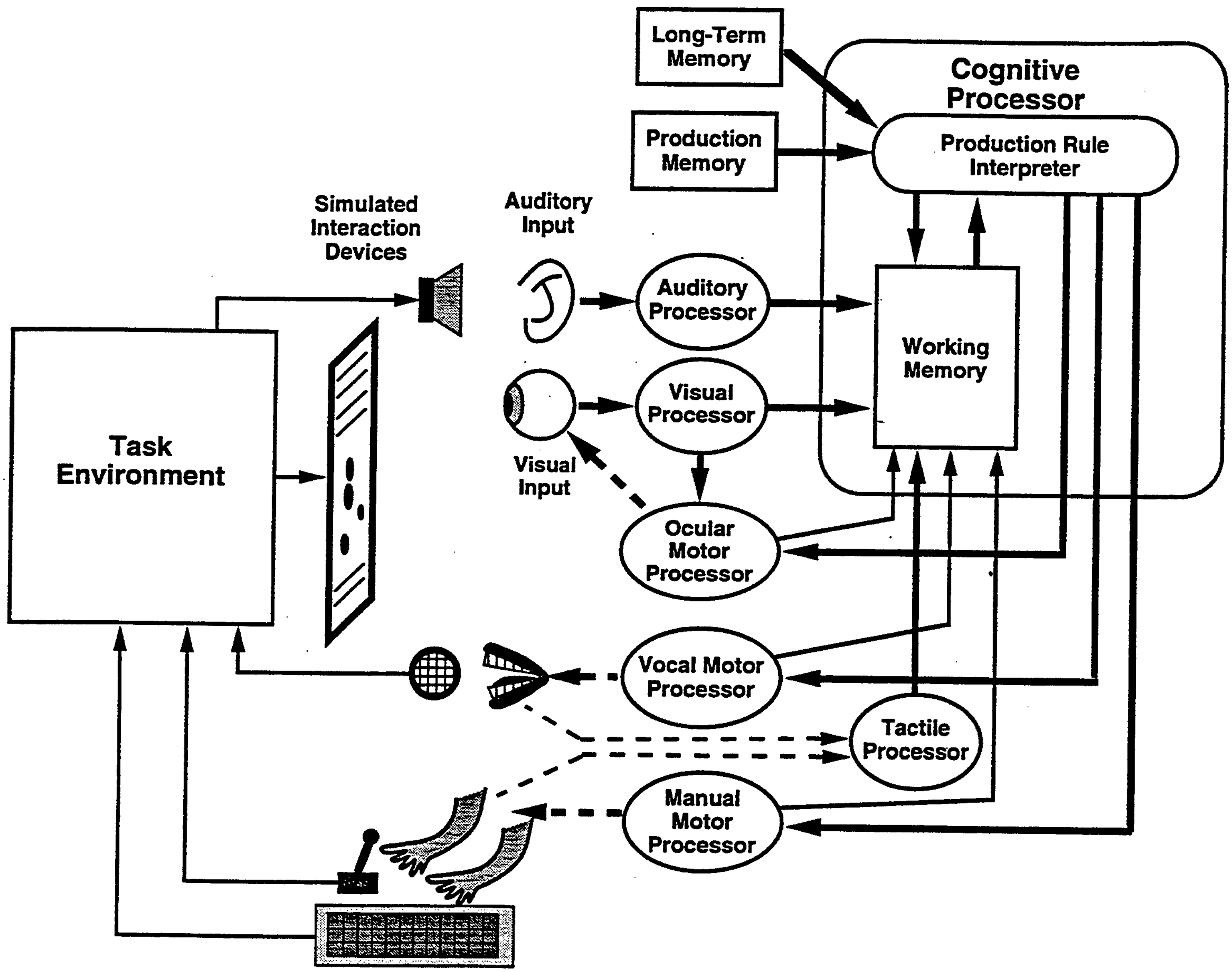

Figure 7. Overview of the information-processing components in the Executive-Process Interactive Control (EPIC) architecture.

Relation to The Model Human Processor. In some respects, EPIC resembles the Model Human Processor (MHP) introduced by Card et al. (1983) for human-computer interaction. Both the MHP and EPIC include a long-term memory, working memory, perceptual processors, cognitive processor, and motor processors. Some of these components are similar in the two architectures.

However, there are crucial differences between EPIC and the MHP. Whereas the MHP was never formally implemented in a computational model, EPIC has been. Unlike the MHP's perceptual and motor processors, those of EPIC are specified in relatively great detail. Also, the cognitive processor in our initial version of EPIC has much more processing capacity than does the MHP's. Consequently, EPIC provides a richer and more instructive treatment of human multiple-task performance.

Assumptions About EPIC's Components

For each of EPIC's components, we make explicit assumptions about the symbolic representations, input/output transformations, and process durations needed to model human performance. Our assumptions are guided by a desire to have EPIC be parsimonius, precisely specified, and consistent with available empirical data (e.g., Atkinson et al., 1988; Boff, Kaufman, & Thomas, 1986; Meyer & Kornblum, 1993). In the following subsections, the assumed properties of EPIC's perceptual processors, motor processors, working memory, and cognitive processor are outlined. A summary of these properties also appears in Table 1.

Perceptual Processors

Our assumptions about EPIC's perceptual processors concern three of their properties: (1) the temporal relations among perceptual operations and activities of other processing units; (2) the forms of input and output used for stimulus detection and identification: (3) the magnitudes of processing times taken in going from input to output. For present purposes, simple table-lookup is used by the perceptual processors in transforming sensory inputs to symbolic perceptual outputs (e.g., stimulus identities). We have not yet implemented complex pattern-recognition algorithms as part of the perceptual processors, because this is not necessary to achieve our current theoretical objectives.

Temporal relations. EPIC's perceptual processors provide direct "pipelines" between the external environment and working memory. For each modality (e.g., vision, audition, and touch), transformations from sensory inputs to perceptual outputs occur asynchronously, in parallel with operations by the cognitive and motor processors. Sensory inputs may enter the perceptual processors at any moment; perceptual outputs are temporally offset from the inputs by parametrically specified amounts of time.

Forms of input and output. The inputs to EPIC's perceptual processors are assumed to be physical stimuli (i.e., categorizable objects and events) presented through simulated display devices (e.g., a virtual CRT screen) for each relevant sensory modality (e.g., vision, audition, and touch). After a stimulus arrives at a perceptual processor, the processor sends symbol strings to working memory, first indicating that a stimulus has been detected in a particular modality (e.g., `AUDITORY DETECTION ONSET`), and later specifying its identity (e.g., `AUDITORY TONE 800 ON`). Symbols denoting other relevant stimulus features (e.g., size, shape, color, loudness, etc.) may also be placed in working memory by the perceptual processors.

Perceptual transmission times. In our EPIC models, parameter values are assigned to the times taken by each perceptual processor for sending stimulus detection and identification symbols to working memory. Typically, the detection times would be rather short and depend on factors such as stimulus intensity and sensory modality, consistent with RTs from simple-reaction experiments (e.g., Woodworth & Schlosberg, 1954). Consistent with RTs from choice-reaction experiments, the identification times would be somewhat longer, vary as a function of stimulus discriminability, and perhaps exhibit a different pattern of modality effects than detection times do. As discussed later, the exact values of these parameters are determined either from representative measurements reported in past literature or from estimates provided by data sets being modeled at the moment.

Table 1

Assumptions about Components of The EPIC Architecture

Type of Component	Assumed Properties
perceptual processors	operations are parallel and asynchronous stimulus identities sent to working memory transmission times depend on modality, intensity, and discriminability
motor processors	response identities received as inputs movement features prepared for physical outputs feature preparation done serially with set time increments advance feature preparation done for anticipated responses movement initiation done after feature preparation efference copies of motoric representations sent to working memory
cognitive processor	programmed with production rules (IF CONDITION, THEN ACTION) rules interpreted by Parsimonious Production System conditions refer to goals, steps, and notes in working memory steps in conditions govern flow of control complex conflict-resolution criteria and spreading activation not used actions regulate working memory and perceptual-motor processors cyclic operation with set mean cycle duration no limit on number of rules being tested and applied simultaneously
working memory	contents consist of goals, steps, and notes contents used and managed by cognitive processor capacity and duration sufficient for performance in PRP procedure

Role of attention. In EPIC, the perceptual processors also depend on one basic type of "attention." Through actions directed by the cognitive and motor processors, virtual physical sensors may be oriented to facilitate the acquisition of sensory information. For example, EPIC's eyes may be moved to look at particular locations and objects in space. We assume that the speed and accuracy with which visual information reaches working memory is a function of the "retinal zone" on which it falls. In this sense, EPIC has properties related to early-selection theories of attention.

Initially, however, we have omitted assuming that perceptual information processing is modulated by internal selective filters. As of yet, for example, no "attentional spotlight" distinct from the spatial fixation of the eyes has been incorporated in EPIC's visual perceptual processor (cf. Beck & Ambler, 1973; Duncan, 1981; Eriksen & St. James, 1986; Eriksen & Yeh, 1985; Jonides, 1980; Posner, 1980; Remington & Pierce, 1984; Shaw & Shaw, 1977; Tsal, 1983). In this sense, EPIC has properties related to late-selection theories of attention. Our tentative omission of an attentional spotlight is motivated by a desire to start with as few "central" bottlenecks as possible in the architecture, so that we may determine to what extent apparent limits on multiple-task performance can be attributed instead to peripheral structural constraints (e.g., finite numbers of physical sensors and effectors) and to people's optional strategies for satisfying task instructions. Nevertheless, if need be, selective filters (Broadbent, 1958) or attenuators (Treisman, 1960) can, of course, be programmed into subsequent versions of EPIC's perceptual processors.

Motor Processors

For EPIC's motor processors, we likewise make assumptions about the forms of input that they receive, the transformations that they perform , and the forms of ouput that they produce. As in perception, these transformations are assumed to take specified amounts of time, depending on their degree of complexity. Explicit constraints are also placed on the degree to which different movements produced by the same motor processor may be independent of each other.

Response symbols and movement features. The inputs to the motor processors are assumed to be symbols that represent the abstract identities of responses (e.g., `LEFT-INDEX`) selected by the cognitive processor. The motor processors transform the response symbols to output commands that control simulated physical effectors (e.g., fingers on right and left hands), which in turn operate simulated external devices (e.g., a virtual response keyboard). Consistent with past studies of manual, vocal, and ocular motor programming (e.g., Abrams & Jonides, 1988; Gordon & Meyer, 1984; Meyer & Gordon, 1985; Rosenbaum, 1980; Yaniv, Meyer, Gordon, Huff, & Sevald, 1990), this transformation involves preparing movement features appropriate to the intended response modality. For example, these features might respectively specify the hand and finger (e.g., `LEFT`, and `INDEX`) to be used in a manual keypress, or the place and manner of articulation (e.g., `LABIAL`, and `STOP`) to be used in the initial consonant of a vocal syllable. The feature specification determines which effector is actually moved.

Serial feature preparation and movement initiation. Likewise consistent with some past research on human motor programming (e.g., Abrams & Jonides, 1988; Gordon & Meyer, 1984; Meyer & Gordon, 1985; Rosenbaum, 1980; Yaniv et al., 1990), EPIC's motor processors prepare movement features serially before the movements are initiated and executed physically. The preparation of each feature is assumed to take an increment of time whose value constitutes a specified parameter of our models. After feature preparation has been completed, a subsequent initiate operation by the relevant motor processor starts overt movement. Thus, upon receiving a response symbol as input, the time taken by a motor processor to start overt movement would equal a sum of individual feature-preparation times and the duration of the initiate operation.[9]

[9] Contrary to what we claim, reservations might be raised about EPIC's assumed serial movement-feature preparation. Results of some past research suggest that feature preparation can occur in parallel for multiple movement features and/or consume lesser amounts of time per feature than embodied by the present motor-processor parameters (Goodman & Kelso, 1980; Ghez, Hening, & Favilla, 1990). Nevertheless, the original studies cited above support our claims, and we have found that the assumptions made here help provide extremely good quantitative fits to data from multiple-task performance in a variety of situations.

Anticipatory movement-feature preparation. On some occasions, the time increment that a motor processor contributes to overt RTs may be reduced through anticipatory movement-feature preparation. We assume that EPIC's cognitive processor enables such preparation by providing a motor processor with advance information about anticipated features of a forthcoming movement. For example, if the next response is expected to be a right-hand keypress, then the manual motor processor may be informed about this ahead of time, and it may program the hand feature early, before receiving later information about what the response's other required features are. This opportunistic programming decreases the additional time that the motor processor has to take after it receives the final response symbol, consistent with previous studies of anticipatory movement preparation (e.g., Coles, Gratton, Bashore, Eriksen, & Donchin, 1985; Meyer, Osman, Irwin, & Yantis, 1988c; Meyer, Yantis, Osman, & Smith, 1984, 1985; Miller, 1982; Osman, Bashore, Coles, Donchin, & Meyer, 1992; Rosenbaum & Kornblum, 1982).[10]

Motor-processor memory buffer. In order to prepare for movements, and to benefit from repetitions of successive responses, EPIC's motor processors have memory buffers that retain recently programmed movement features. The buffers' contents remain until they are deleted by the cognitive processor or changed for another future movement. Stored features from past movements can be reused if some of them match those needed next. For example, if the next desired movement is identical to the immediately prior one, it may be produced simply by having the motor processor start an initiate operation, reusing all the movement features already in its buffer. As a result, response-repetition effects like those found in choice RTs (Kornblum, 1973) can be obtained.

Efference copy. As part of movement preparation and initiation, it is assumed that EPIC's motor processors send efference copies of their inputs, intermediate status, and outputs back to working memory in the form of symbolic representations. These representations may be used by the cognitive processor for monitoring and regulating the progress of on-going system operations, as previous studies of perceptual-motor interaction, response adjustment, and error correction have suggested (e.g., Gehring, Goss, Coles, Donchin, & Meyer, 1993; von Holst & Mittelstaedt; 1950).

Unitary manual motor processor. Finally, another crucial property of EPIC's manual motor processor should be emphasized. It is a unitary component that produces movements by both the right and left hands; each hand does not have a separate independent controller. As a result, interference between two concurrent tasks can occur when they respectively require responses with the right and left hands, even though the two hands themselves are physically separate. Supporting these assumptions, manual-manual tasks have been found to yield substantially more interference than do manual-vocal tasks in at least some multiple-task situations (e.g., McLeod, 1977; Pashler, 1990).[11]

Working Memory

EPIC's working memory is characterized by assumptions about the form, amount, and durability of its contents. Regarding these assumptions, our intent here is to have EPIC be as simple as possible and to place minimal a priori limits on the putative capacity of central processes. Strict adherence to this heuristic lets us better assess the extent to which human multiple-task performance is limited by other factors, such as peripheral structural constraints.

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[10] For some situations, such as "simple" reactions involving one S-R pair, it is possible that all of the required movement features are programmed in advance before stimulus onset occurs. If so, then producing an overt response after detecting the stimulus onset would merely entail having the cognitive processor instruct the appropriate motor processor to issue a movement-initiation command without further ado.

[11] Interference typically occurs when the responses for each of two manual tasks must be produced at different times by different hands. However, under conditions in which left-hand and right-hand responses are initiated simultaneously, they will not necessarily interfere as much with each other. As described later, we have modeled the latter possibility through a compound-response style that EPIC's manual motor processor uses on occasions where response grouping takes place.

Form of contents. We assume that working memory contains information produced through operations by the perceptual, cognitive, and motor processors. This information includes *task goals*, *steps* (sequential control flags), and *notes* (e.g., stimulus-identity symbols, response-identity symbols, efference copies of motor-processor status reports, and task strategies). They provide the basis on which the conditions of production rules are tested for successful matches with the present state of the system.

Amount and durability of contents. Following heuristic principles mentioned earlier, we also assume for now that working memory has sufficient capacity and durability to preserve all of the information needed in elementary multiple-task situations such as the PRP procedure. The initial version of EPIC includes no explicit mechanisms of information decay or overflow (cf. Anderson, 1976, 1983, 1993; Atkinson & Shiffrin, 1968; Baddeley, 1986; Card et al., 1983). Items are deleted from working memory if and only if the actions of particular cognitive-processor production rules specifically do so.[12]

Cognitive Processor

Our assumptions about EPIC's cognitive processor concern how it is programmed and what its temporal properties are during the performance of single and multiple tasks.

Production-rule programming. We assume that the cognitive processor is programmed with production rules stored in procedural memory. To ensure that the conditions and actions of these rules are simple and explicit, they conform to the syntax of the Parsimonius Production System (PPS) mentioned earlier (Covrigaru & Kieras, 1987; also see Bovair et al., 1990).

Representation of rule conditions. The conditions of the production rules are symbol strings that refer to goals, steps, and notes stored in working memory. Goals consist of items (e.g., `GOAL DO TASK 1`) that enable the performance of particular tasks to proceed. Steps consist of items (e.g., `STEP DO CHECK FOR TONE 800`) that help control exactly when a rule has its actions executed during the course of task performance. Notes consist of items that keep track of inputs and outputs by the perceptual, cognitive, and motor processors; they contain information about the status of test trials (e.g., `TRIAL UNDERWAY`), task progress (e.g., `TASK 1 DONE`), stimulus identities (e.g., `AUDITORY TONE 800 ON`), response identities (e.g., `RESPONSE IS LEFT-INDEX`), and task strategies (e.g., `STRATEGY TASK 1 IS IMMEDIATE`).

Representation of rule actions. The actions of the production rules contain instructions for updating the contents of working memory and programming EPIC's motor processors. Working memory is updated by adding and deleting goals, steps, and notes in the memory data base (e.g., `ADD (STEP WAIT FOR TASK 1 RESPONSE COMPLETION);DEL (AUDITORY TONE 800 ON)`). Motor-processor instructions consist of commands (e.g., `SEND-TO-MOTOR (MANUAL PERFORM LEFT-INDEX)`) that direct subsequent movement preparation and initiation.

Tests of rule conditions and execution of rule actions. During operation of EPIC's cognitive processor, production-rule conditions are tested by the PPS interpreter. If, at some moment, these tests indicate that all the conditions of a particular rule match the current contents of working memory, then the interpreter immediately executes all the rule's actions. For example, suppose that in Task 1 of the PRP procedure, a keypress with the left-hand index finger should be made immediately when an 800 Hz stimulus tone is presented. Then the cognitive processor might use the following rule:

[12] Of course, the present assumptions about working memory may not suffice more generally. Significant capacity limits on the verbal articulatory loop, as well as other forms of temporary storage, have already been demonstrated in more complex multiple-task situations (e.g., Baddeley, 1986). Thus, our initial version of EPIC will have to be modified and elaborated in future theoretical work. Some ways in which we might do so are outlined elsewhere (Kieras & Meyer, 1996).

```
IF
 ((GOAL DO TASK 1)
  (STRATEGY TASK 1 IS IMMEDIATE)
  (AUDITORY TONE 800 ON)
  (STEP DO CHECK FOR TONE 800))
THEN
 ((SEND-TO-MOTOR (MANUAL PERFORM LEFT INDEX))
  (ADD (TASK 1 RESPONSE UNDERWAY))
  (ADD (STEP WAIT FOR TASK 1 RESPONSE COMPLETION))
  (DEL (STEP DO CHECK FOR TONE 800))
  (DEL (AUDITORY TONE 800 ON))).
```

In order for this rule to apply, the contents of working memory must match four conditions. The first relevant condition is "GOAL DO TASK 1", for which a corresponding item would be put in working memory at the start of each trial during the PRP procedure, thereby enabling progress on Task 1 to proceed. The second relevant condition is "STRATEGY TASK 1 IS IMMEDIATE", for which a corresponding item would also be put in working memory at the start of each trial, thereby indicating that a Task 1 response should be produced as soon as it is selected. The third relevant condition is "AUDITORY TONE 800 ON", for which a corresponding item would be put in working memory by EPIC's auditory perceptual processor when it identifies the stimulus tone. The fourth relevant condition is "STEP DO CHECK FOR TONE 800", for which a corresponding item would be put in working memory during the Task 1 response-selection process. If and when the contents of working memory match all four of these conditions at the same time, then the above rule's five actions would be executed simultaneously. As a result, the action "SEND-TO-MOTOR (MANUAL PERFORM LEFT INDEX)" would instruct the manual motor processor to prepare and initiate a movement by EPIC's left index finger. The actions involving "ADD" instructions would add the items "TASK 1 RESPONSE UNDERWAY" and "STEP WAIT FOR TASK 1 RESPONSE COMPLETION" to working memory, while the actions involving "DEL" would delete the items "STEP DO CHECK FOR TONE 800" and "AUDITORY TONE 800 ON".

Cyclic operation. We assume that the cognitive processor operates in a cyclic fashion, with no pause between the end of one cycle and the beginning of the next. During each cognitive-processor cycle, three types of operation take place. First, the contents of working memory are updated to incorporate the results of activities completed by the perceptual, cognitive, and motor processors during the immediately preceding cycle. Second,the conditions of production rules are tested to determine which ones match the current contents of working memory. Third, the actions of rules whose conditions pass these tests are executed.

The cognitive-processor cycles are not synchronized with external stimulus and response events. Inputs from the perceptual processors are accessed only intermittently, after working memory is updated at the start of each cycle. Any input that arrives during the course of a cycle must therefore wait temporarily for service until the next cycle begins. This is consistent with the temporal granularity of perceived stimulus sucessiveness (Kristofferson, 1967), the spectral characteristics of simple RT distributions (Dehaene, 1992, 1993), and the periodicity of EEG brain activity (e.g., alpha rhythms; Callaway & Yeager, 1960; Kristofferson, 1967; Ray, 1990).

Inherent parallelism. On each cognitive-processor cycle, the PPS production-rule interpreter tests the conditions of all rules stored in procedural memory. For every rule whose conditions match the current contents of working memory, its associated actions are all executed in parallel at the end of the cycle. The durations of the cognitive processor's cycles do not depend on the number of production rules involved. EPIC imposes no upper limit on how many rules may have their conditions tested and actions executed at the same time. This radical feature means that in our simulations of multiple-task performance, there is no "hardwired" central-processing bottleneck to impede operations such as response selection and other decision making for concurrent tasks. When simulating subjects' performance under the PRP procedure, for example, EPIC's cognitive processor can select responses simultaneously for both Task 1 and Task 2. Such capabilities may lead us instead to identify and describe other alternative performance limitations, including conservative task strategies and structural constraints on perceptual or motor processors. Even if some of our initial assumptions in EPIC are wrong, they can still provide significant inspiration for further conceptual analysis and empirical data collection.

Modeling Human Performance With EPIC

To use EPIC for constructing computational models of human performance, two complementary steps are necessary. First, we must consider how various individual tasks might be performed, if our architectural assumptions are correct. Second, we must consider how individual tasks might be coordinated during multiple-task performance.

Single-Task Performance

With the present theoretical framework, it is straightforward to model the performance of individual perceptual-motor and cognitive tasks. We begin by analyzing the information-processing requirements of each task at hand. On the basis of an initial task analysis, the following details are specified: (1) a set of production rules to be used by EPIC's cognitive processor in performing the task; (2) the initial contents of working memory needed for matching the conditions of these rules; and (3) stimulus inputs from the external environment that get the task started.

To help achieve consistency, generality, and testability in our modeling, we also impose other meta-theoretical constraints: (1) the properties of EPIC's cognitive, perceptual, and motor processors remain the same across all tasks; (2) the production rules used to program the cognitive processor may differ across tasks, but within a task, these rules remain constant unless an explicit learning algorithm (e.g. Anderson, 1982; Bovair et al., 1990) is included to describe practice effects.

Heuristics for production-rule specification. There are several supplementary heuristics through which the rules for performing a particular task may be specified more fully. They come from carefully examining the goals of the task and the instructions that people receive about how to achieve them. For example, task instructions may dictate which parts of a task should be performed first, and what subgoals have relatively high or low priority. We assume that on the basis of such considerations, people tend to compile a set of production rules that constitute an efficient way of performing a given task, subject to inherent human information-processing capacities and limitations. This "rationality principle" has proven fruitful in past analyses of both cognitive and perceptual-motor performance (e.g., Anderson, 1990; Card et al., 1983; Meyer, Abrams, Kornblum, Wright, & Smith, 1988a; Meyer, Smith, Kornblum, Abrams, & Wright, 1990); it may likewise have merit here.

Treatment of basic factor effects. The production rules used by EPIC's cognitive processor to perform particular tasks are also specified such that they mimic certain basic factor effects on RTs. Some factors that significantly affect RTs in single-task and multiple-task situations include the numerosity, compatibility, and repetition of S-R pairs (for a review, see Sanders, 1980). We characterize these effects by changing the number of production-rule steps, and hence the number of cognitive-processor cycles, that take place during each trial, depending on the levels of relevant task factors. For example, our subsequent account of the S-R numerosity effect in the PRP study by Karlin and Kestenbaum (1968) assumes that response selection with an ensemble of five alternative S-R pairs took more processor cycles than were taken with two S-R pairs.

Our accounts of S-R repetition effects are achieved likewise. In particular, the production-rule sets used by EPIC's cognitive processor incorporate a repetition-by-pass feature such that whenever the same stimulus occurs again on the next trial, then the same response as before is selected immediately for it. This accords with proposals by previous theorists about the source of repetition effects (e.g., Keele, 1973; Kornblum, 1973; Pashler & Baylis, 1991; Theios, 1973).

We adopt a similar tack in characterizing S-R compatibility effects. If a task involves compatible stimuli and responses (e.g., right and left arrows associated respectively with right and left hand movements), then in our models, a perceptual processor may produce a stimulus-identity code whose features are isomorphic to ones used by a motor processor for programming response movements. Consequently, the cognitive processor may pass this code directly to the motor processor, reducing the processor cycles taken for response selection, and thereby decreasing overall RT. This is consistent with other accounts of compatibility effects (e.g., Kornblum et al., 1990).

Through the same approach, it is possible to characterize other factor effects as well, including ones that stem from stimulus probability (Miller & Pachella, 1973) and response competition (e.g., Stroop, 1935). Our principal objective, however, is not just to focus on single-task performance. Rather, we seek a detailed general account of human multiple-task performance.

Multiple-Task Performance

The crucial next step entails specifying how the functions performed by the distinct sets of production rules for each of two or more concurrent tasks are coordinated. Such coordination is essential under EPIC. Given that EPIC's cognitive processor has the capacity to test the conditions and execute the actions of many rules in parallel, it can make progress on several tasks at once, as if each task were being performed alone. However, for every task to get completed properly, there must be some supervisory control to ensure that the tasks' production-rule sets do not try to use the same physical sensors (e.g., eyes) or effectors (e.g., hands) simultaneously in conflicting ways. Also, supervisory control is needed to ensure that performance obeys instructions about relative task priorities.

Executive processes. In our computational models, we satisfy these needs by incorporating executive processes whose functions are performed by additional sets of production rules distinct from those for the individual tasks. The executive processes maintain task priorities and coordinate progress on concurrent tasks through various types of supervisory control. For example, they insert and delete task goals in working memory, direct the eyes to look at one place or another in visual space, send selected responses either to motor processors or working memory, and prepare movement features of anticipated responses, all depending on the current-context and task instructions. What we propose here is therefore similar in some respects to ideas formulated by previous theorists who have emphasized the importance of executive processes (e.g., Baddeley, 1986; Duncan, 1986; Logan, 1985; Norman & Shallice, 1986; Shallice, 1972).

Nevertheless, the executive processes of our models have a form significantly different from ones in past verbal theories. We specify the details of these processes precisely with well-defined sets of production rules, whose format and application parallel the rule sets used to perform individual tasks. This lets us achieve a considerable degree of architectural homogenity. Under the present architecture, there is no structurally separate supervisory-control mechanism, whereas such mechanisms are the *sine qua non* of some theories (e.g., the *Supervisory Attentional System*; Norman & Shallice, 1986).

There are also some additional important properties of the executive processes in our models: (1) they do not contain procedural knowledge sufficient to perform any individual task; (2) they do not modify the individual tasks' production rules; (3) they coordinate progress on individual tasks only by manipulating goals and notes in working memory; (4) they may change as a function of particular task combinations, priorities, experimental paradigms, and subjective strategies; (5) they allow the production-rule sets for individual tasks to be used across a variety of multiple-task situations.

Scheduling algorithms. With the executive processes proposed here, performance of concurrent tasks may be coordinated through various scheduling algorithms. For example, one such algorithm is *lockout scheduling*. Under it, tasks are performed one by one in strict sequence; each successive task remains entirely suspended (i.e., "locked out") until its turn for processing comes. This progression is achieved by having the executive process insert and delete the tasks' main goals one after another in working memory. Cross-task coordination then has much the same temporal character as under the global single-channel hypothesis, but the seriality of performance stems from optional supervisory control, rather than from one task inherently blocking another task's entry into a single information-processing channel.

Lockout scheduling has the virtue of being simple and easy to implement. It requires a relatively minimal executive process, and provides a type of coordination that novice multiple-task performers might favor because of its conservative nature, which eliminates potential conflicts over access to perceptual-motor components. However, lockout scheduling has disadvantages too. It precludes highly efficient multiple-task performance, because no temporal overlap is allowed in the performance of two or more tasks, even though such overlap might be possible from the standpoint of available system resources. Thus, other scheduling algorithms also merit further consideration here. (For more discussion of production systems that involve lockout scheduling, see Newell, 1980).

A second possible algorithm for cross-task coordination is *interleaved scheduling* (Schweickert & Boggs, 1984). Under it, some of the component processes for multiple tasks are allowed to proceed concurrently; an individual task is suspended only during minimal time periods when unavoidable conflicts with competing tasks might otherwise occur. This requires a more complex executive process whose production rules are highly specific to particular task combinations. Consequently, interleaved scheduling might emerge in the strategic repertoire of expert performers only after substantial practice. Indeed, a major contribution of practice at multiple-task performance perhaps involves enabling a shift from lockout scheduling to fully interleaved scheduling.

A Model of Performance for The PRP Procedure

As an instructive illustration of how the present theoretical framework may be used to model human multiple-task performance, subsequent sections of this article focus again on one particular paradigm: the PRP procedure. For performance observed under this procedure, we propose an explicit computational model based on our production-system formalism and EPIC information-processing architecture. Using their capabilities, our proposed model accounts for a variety of quantitative results from the PRP procedure and leads to interesting new predictions as well.

Our choice of focus has several motivations. First and foremost, the PRP procedure involves a very basic multiple-task situation. People who perform under it must deal with two discrete well-defined tasks; the ensembles of stimuli and responses, the order of stimulus presentation, and the task priorities (required response order, speed, and accuracy) are prespecified clearly. Any worthy computational model should therefore be applicable to this situation.

Another attractive feature of the PRP procedure is that past studies with it have yielded many systematic quantitative results, including the PRP effect, PRP curves (i.e., functions of Task 2 RT versus stimulus-onset asynchrony), and various factor effects on them (e.g., Bertelson, 1966; Kantowitz, 1974; Pashler, 1994a; Smith, 1967; Welford, 1967). These results provide a challenging data base with which to test EPIC's explanatory power and conceptual fertility. In addition, the PRP procedure has some similarity to real-world situations involving human multiple-task performance, such as aircraft-cockpit operation and air-traffic control. Thus, by dealing with this procedure at the outset, we may set the stage for extending our theoretical framework to other relevant contexts.

The Strategic Response-Deferment Model

The specific computational model that we propose here is called the *strategic response-deferment (SRD) model*. In what follows, its assumptions are introduced briefly, and their general rationale is presented.

Basic assumptions. According to the SRD model, when the SOA is short, stimulus identification and response selection for Task 2 of the PRP procedure may proceed at the same time as Task 1 is being performed. The start of Task 2 response selection does not necessarily have to wait until Task 1 response selection has been completed. Temporal overlap of these response-selection processes is achieved through EPIC's cognitive processor, which has the capacity to test and apply distinct sets of production rules in parallel.

Furthermore, in order that overt Task 2 responses do not occur prematurely after they have been selected, the SRD model assumes that at short SOAs, selected Task 2 responses are sometimes stored temporarily in working memory, rather than being sent directly to their motor processor for immediate output. It is this optional strategic deferment of selected Task 2 responses that gives the model its name. Response deferment is assumed to be supervised by an executive process that controls when selected Task 2 responses are released after sufficient Task 1 progress has occurred. Such control efficiently precludes conflicts over the use of the same motor processor, and it helps satisfy instructions typically associated with the PRP procedure.

Rationale. Several complementary considerations motivate the SRD model. Consistent with proposals by some previous theorists (e.g., Allport, 1980a, 1987; Neisser, 1976; Neumann, 1987), it seems likely that performance decrements under the PRP procedure stem at least partly from optional strategies adopted to satisfy task priorities and to avoid perceptual-motor conflicts, rather than from permanent central bottlenecks in response selection and other decision processes. PRP instructions strongly encourage subjects to make Task 1 "primary" and to produce Task 1 responses first, before finishing Task 2; this encouragement is reinforced by having uniformly non-negative SOAs (e.g., see McCann & Johnston, 1992; Pashler, 1984; Pashler & Johnston, 1989). Even if there is ample central-processing capacity for concurrent response selection in both tasks, these nuances of the PRP procedure could bias subjects to adopt partial lockout scheduling of some peripheral processes in Task 2, thereby manifesting a PRP effect.

Yet subjects may still try to use their available processing resources to the maximum extent possible, given whatever the task instructions and perceptual-motor limitations are. Thus, they may engage in simultaneous stimulus-identification and response-selection processes for multiple concurrent tasks under the PRP procedure, as the SRD model assumes. If so, then the present theoretical framework -- with its flexible programmable cognitive processor and battery of fixed perceptual-motor processors -- should let us account aptly for results from a variety of PRP studies.

Components of the SRD model. More specifically, what are the components of the SRD model? Following previous discussion, the answer is straightforward. The SRD model has two distinct sets of production rules for Task 1 and Task 2 of the PRP procedure. Also included as part of the model is a third production-rule set for the executive process that coordinates the two tasks.

Production Rules for Task Processes of SRD Model

Several functions are performed by the SRD model's production rules for Tasks 1 and 2. In the following subsections, we describe these functions more fully.

Task 1 production rules. The Task 1 production rules do task initiation, response selection, repetition by-pass, and task completion when a Task 1 stimulus is presented. For example, *Appendix 1* illustrates a set of such rules that make choice reactions in the case of an auditory/manual Task 1. Application of these rules proceeds as information passes through the components of the EPIC architecture, leading from stimulus to response. At the onset of the Task 1 stimulus, a perceptual processor detects it and puts a detection symbol (e.g., `AUDITORY DETECTION ONSET`) in working memory after some perceptual transmission time. This triggers the task-initiation rules, which place notes in working memory to indicate that Task 1 is now underway and that response selection may proceed as soon as the Task 1 stimulus has been identified. Next, after a while longer, the perceptual processor sends a stimulus-identity symbol (e.g., `AUDITORY TONE 800 ON`) to working memory, indicating exactly what the Task 1 stimulus is. This enables a series of steps during which the Task 1 response-selection rules decide what the identity of the appropriate Task 1 response is.[13] Ordinarily, one of the selection rules then sends a response symbol (e.g., `MANUAL PERFORM LEFT-INDEX`) directly to its appropriate motor processor; as explained later, however, it is possible instead that the selected response symbol could be put temporarily in working memory. The response-selection rules also have a repetition by-pass feature, whereby if a Task 1 stimulus is

[13] In principle, the form and content of the response-selection rules may stem from an initial skill-acquisition process that converts declarative knowledge to procedural knowledge about how the tasks should be performed (Anderson, 1982). Requisite declarative knowledge could be obtained through the PRP procedure's verbal task instructions. For example, the instructions might state that "if the tone is low pitched, then press the left middle-finger key; if the tone is high pitched, then press the left index-finger key." When given these instructions during practice under the PRP procedure, the skill-acquisition process might convert them to two production rules that are stepped through successively.

the same as what occurred on an immediately preceding trial, then the prior Task 1 response is selected at once as the current desired one. Consistent with heuristic principles outlined previously, the response-selection rules are defined such that the mean number of cognitive-processor cycles taken by the selection process depends directly on factors such as S-R numerosity and compatibility (cf. Footnote 3). After the selected Task 1 response has been sent to its motor processor, the task-completion rules wait until movement production has progressed sufficiently far for Task 1 to be declared done. In particular, this latter state may be reached when the motor processor signals that all of the movement features for the Task 1 response have been prepared and movement is about to be initiated overtly.[14] Upon receipt of the motor processor's signal, the task-completion rules put "TASK 1 DONE" in working memory, and they finish terminal book-keeping activities (e.g., deleting "GOAL DO TASK 1" and other ancillary notes from working memory).

Task 2 production rules. The production rules for Task 2 perform functions like those of the Task 1 rules, leading from the Task 2 stimulus to the Task 2 response. However, as mentioned before, the two task rule sets are modular; neither set "knows" about the content or status of the rules in the other. To be specific, the Task 2 rules are defined solely to deal with the stimulus modality, response modality, and S-R associations relevant in performing Task 2. For example, *Appendix 2* outlines a set of production rules that accomplish response selection and other ancillary functions in a Task 2 that requires visual-manual choice reactions.

Alternative response-transmission modes. Another crucial feature of the production rules used by the SRD model for performing each task of the PRP procedure is that they have two alternative response-transmission modes: immediate, and deferred. With them, access to EPIC's motor processors can be managed flexibly, enabling efficient strategies that optimally satisfy task instructions. Also, potential conflicts between tasks that require access to the same motor processor (e.g., a left-hand Task 1 and a right-hand Task 2) can be avoided.

The *immediate transmission mode* is used in performing a task that has the current highest priority for response output (e.g., in the PRP procedure, Task 1 at short SOAs, and Task 2 at long SOAs, after Task 1 has been completed). The SRD model's executive process invokes immediate mode by placing the note "STRATEGY TASK N IS IMMEDIATE" in working memory, which may then be matched with the conditions of production rules that do immediate-mode response selection and transmission. When a task's rules are applied in immediate mode, they send the products of response selection (i.e., symbols for selected responses) directly to the relevant motor processor, where corresponding movement features are prepared and overt responses are initiated without further ado. For example, the following production rule, which was also mentioned previously, uses immediate mode in selecting a left index-finger response and sending it to the manual motor processor after an 800 Hz tone during an auditory-manual Task 1:

```
IF
 ((GOAL DO TASK 1)
  (STRATEGY TASK 1 IS IMMEDIATE)
  (AUDITORY TONE 800 ON)
  (STEP DO CHECK FOR TONE 800))
THEN
 ((SEND-TO-MOTOR (MANUAL PERFORM LEFT INDEX))
  (ADD (TASK 1 RESPONSE UNDERWAY))
  (ADD (STEP WAIT FOR TASK 1 RESPONSE COMPLETION))
  (DEL (STEP DO CHECK FOR TONE 800))
  (DEL (AUDITORY TONE 800 ON))).
```

In essence, the immediate mode helps maximize preparation for task completion. Its function may be related to the *sensorial strategy* of performance noted by early introspectionists (Lange,

[14] Alternatively, depending on contextual circumstances, other internal events either before, during, or after the preparation of movement features could serve as a critical juncture at which Task 1 is declared to be "done." Thus, as discussed more fully later, the choice of this juncture is an adjustable parameter in the SRD model.

1888; cf. Meyer et al., 1984). According to Lange (1888; cited by Boring, 1950, pp. 148-149), a subject who adopts the sensorial strategy would "direct the whole preparatory tension towards the expected sense impression, with the intention, however, of letting the motor impulse follow immediately on the apprehension of the stimulus, avoiding any unnecessary delay...." This is exactly what the immediate transmission mode enables.

In contrast, the *deferred transmission mode* is used for performing lower-priority tasks (e.g, Task 2 of the PRP procedure at short SOAs) while higher-priority tasks are underway. The executive process invokes deferred mode by placing the note "STRATEGY TASK N IS DEFERRED" in working memory, which may then be matched with the conditions of production rules that do deferred-mode response selection. When the task's rules operate in deferred mode, they do not send symbols for selected responses directly to a motor processor; instead, the response symbols are put in working memory, where they remain temporarily until it is appropriate for them to be output. This provides a way whereby the production rules of lower-priority tasks may progress as far as possible on response selection yet avoid disrupting or usurping other higher-priority tasks. For example, the following rule uses deferred mode to select a right index-finger response and put it in working memory when the digit "2" appears during a visual-manual Task 2:

```
IF
 ((GOAL DO TASK 2)
  (STRATEGY TASK 2 IS DEFERRED)
  (VISUAL DIGIT 2 ON)
  (STEP DO CHECK FOR VISUAL DIGIT 2))
THEN
 ((ADD (RESPONSE IS RIGHT-INDEX))
  (ADD (STEP WAIT FOR TASK 2 RESPONSE PERMISSION))
  (DEL (STEP DO CHECK FOR VISUAL DIGIT 2))
  (DEL (VISUAL DIGIT 2 ON))).
```

Subsequently, sometime after this rule has been applied, another production rule would send the selected Task 2 response from working memory to its motor processor when permission for the latter transmission is given. Such permission occurs through a process that we call "unlocking," which is described in more detail later.

The deferred transmission mode might play a role in other contexts as well. It provides a natural way to attain intermediate levels of preparation in some types of response-priming procedure, where subjects are told beforehand to prepare for producing a specific response, but must then withhold overt physical movement until a later go-signal occurs (e.g., see Meyer & Gordon, 1985; Meyer et al., 1984, 1985; Rosenbaum & Kornblum, 1982; Yaniv et al., 1990).

Production Rules for Executive Process of SRD Model

In the SRD model, progress on Task 1 and Task 2 of the PRP procedure is coordinated by an executive process of the sort discussed earlier. The executive process has its own set of production rules (e.g., see *Appendix 3*), which together help achieve three objectives: (1) Task 1 responses always precede Task 2 responses; (2) movement preparation and initiation for Task 2 do not usurp the motor processor needed for Task 1; (3) subject to the preceding constraints, Task 2 is completed about as quickly as possible. These objectives are achieved through the strategy outlined in Figure 8. It contains several steps whose temporal arrangement and functions are as follows.

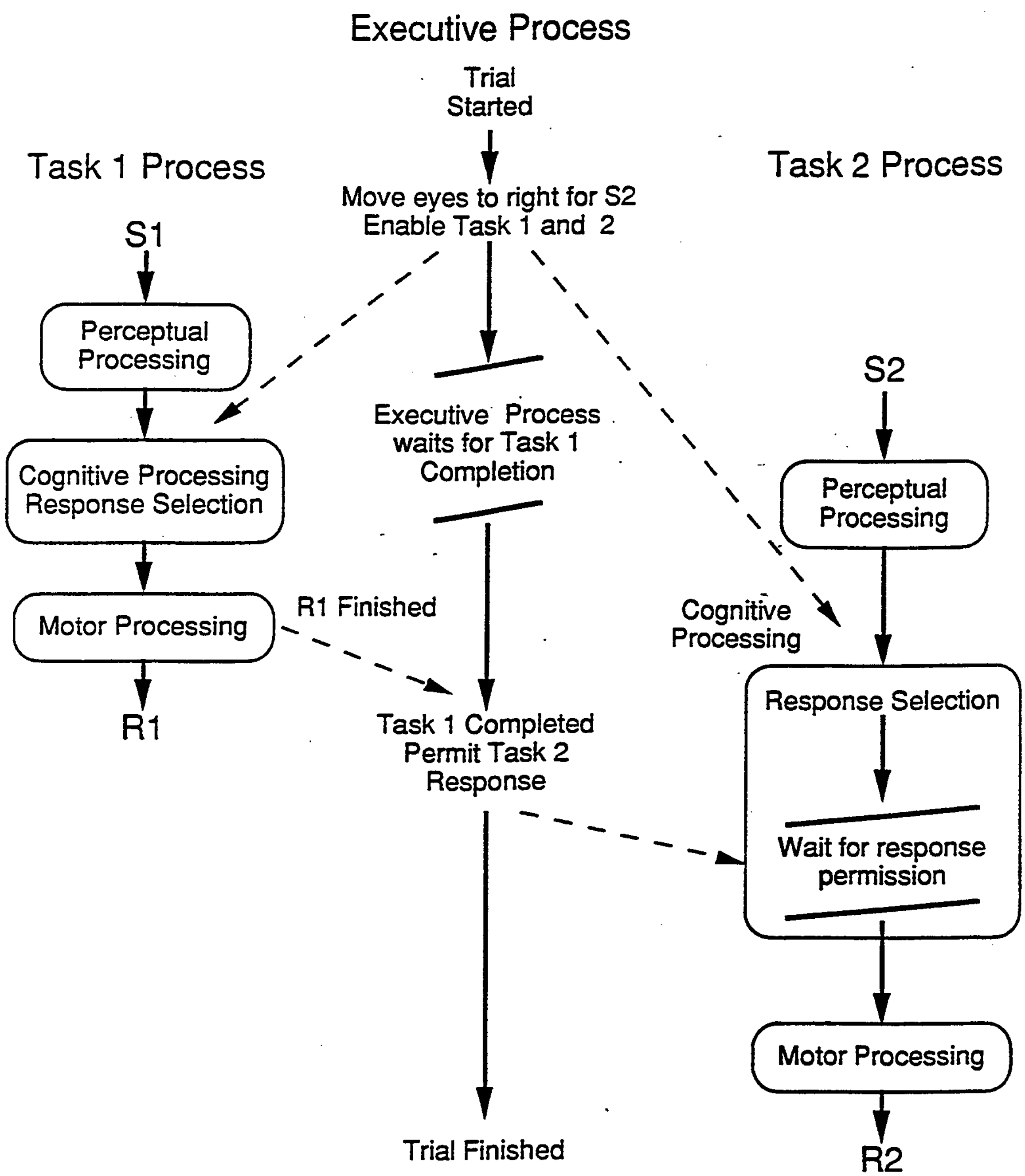

Figure 8. The task-scheduling strategy used by the executive process of the SRD model for the PRP procedure. Here response selection during Tasks 1 and 2 may proceed simultaneously while satisfying task instructions and minimizing mean RTs. Breaks in the vertical time lines indicated by diagonal hash marks represent variable time intervals whose durations depend on the SOA and the temporal properties of prior processes.

Task-rule enablement. At the start of each trial under the PRP procedure, when a warning signal is detected, the first step taken by the SRD model's executive process is to enable both the Task 1 and Task 2 production rules for execution. This involves putting "GOAL DO TASK 1" and "GOAL DO TASK 2" in working memory. Given these goals, response selection may then proceed for each task as soon as the identification of relevant stimuli has been completed by EPIC's perceptual processors.[15]

Transmission-mode initialization. Along with enabling the production rules for each task, the executive process initializes the response-transmission modes to be used during response selection. This involves putting the note "STRATEGY TASK 1 IS IMMEDIATE" in working memory, letting the Task 1 response-selection rules operate in immediate mode. As a result, selected Task 1 responses will be sent directly to their appropriate motor processor, consistent with PRP instructions to make Task 1 primary. Also consistent with these instructions, the executive process puts the note "STRATEGY TASK 2 IS DEFERRED" in working memory, constraining the Task 2 response-selection rules to operate initially in deferred mode. Consequently, Task 2 responses that are selected during early stages of Task 1 will be put in working memory temporarily, rather than being sent directly to their motor processor, thus ensuring that overt Task 2 responses do not occur prematurely. Once placed in working memory, a pending Task 2 response must wait there until the executive process later permits the Task 2 production rules to send it to an appropriate motor processor.

Anticipatory eye movements. At the same time as the executive process enables the task production rules and initializes their response-transmission modes, it also makes anticipatory eye movements so that stimulus perception and response selection may proceed as best possible when either Task 1 or Task 2 is visual. If both tasks involve visual stimuli, and if their stimuli have different spatial locations, then the eyes would first be positioned appropriately for Task 1 because of its higher priority. After perception of a visual Task 1 stimulus has progressed far enough, the eyes would later be repositioned appropriately for a visual Task 2 stimulus. Alternatively, if only the Task 2 stimuli are visual, then the eyes would be positioned appropriately for them at the start of each trial, thereby letting stimulus perception in Task 2 start sooner than might otherwise be the case. Because eye movements take significant amounts of time (e.g., on the order of 200 ms or more for preparation and execution), overt Task 2 RTs can depend substantially on which tasks are visual.

Task-status monitoring. Next, the executive process enters an intermediate phase that involves monitoring the status of Task 1 performance and waiting until it has progressed sufficiently far to be declared "done." During this phase, the Task 1 stimulus is presented and identified, the Task 1 production rules select a response, and the Task 1 response's identity is sent to its motor processor. Depending on the SOA and other relevant factors (e.g., the position of the eyes), progress on Task 2 (i.e., stimulus identification and response selection) may also proceed while Task 1 is underway. For example, if the SOA is short and Task 1 takes a relatively long time, then a Task 2 response may be selected and put in working memory before intermediate task-status monitoring by the executive process ends. On the other hand, if the SOA is long or Task 1 goes quickly, then no Task 2 response may be selected during this period. In any case, eventually a Task 1 production rule will put the note "TASK 1 DONE" in working memory, cuing the executive process to take its next step, an unlocking routine for Task 2.

Task 2 unlocking. The unlocking routine enables previously and subsequently selected Task 2 responses to reach their motor processor for final output. This entails dealing with various possible states of affairs that may arise because Task 2 starts and proceeds temporarily in the deferred response-transmission mode. For example, it is possible that by when Task 1 finishes, either (1) a Task 2 response has already been selected and put in working memory, (2) response selection has started but not been completed for Task 2, or (3) response selection for Task 2 has not yet begun. To deal with the latter alternatives, the executive process takes one or more of several substeps,

[15] As implied by the dashed arrows in Figure 8, the executive process does not directly start or stop perceptual activities for Task 1 and Task 2. Rather, EPIC's perceptual processors operate in parallel with the cognitive processor. Thus, as soon as a test stimulus reaches an appropriate sensor (e.g., the eyes or ears), its perception proceeds autonomously, leading to stimulus identities being put in working memory. Nevertheless, perceptual activities can be controlled indirectly by the executive process, depending on where it focuses EPIC's peripheral sensors (e.g., the eyes).

including *response permission* or *task suspension*, *transmission-mode shifting*, and *task resumption*. A detailed flowchart of these substeps and their time course appears in Figure 9. Which of them is taken during a particular trial depends on exactly how much progress has been made on Task 2 by the time Task 1 is "done."

Upon noticing that the Task 1 production rules have put the note "TASK 1 DONE" in working memory, the executive process chooses between taking the response-permission or task-suspension substep of the unlocking routine. Here it checks whether a Task 2 response has already been selected and stored in working memory during the course of progress on Task 1. If the check has a positive outcome, then the executive process grants permission for the selected Task 2 response to be sent to its motor processor without further delay. Response permission is granted by putting the note "PERMIT TASK 2 RESPONSE" in working memory, which helps satisfy the conditions of another Task 2 production rule that sends previously selected Task 2 responses from working memory to their motor processor.

Alternatively, suppose that a Task 2 response has not been selected yet before Task 1 is "done" and the unlocking routine starts. Then the executive process temporarily suspends Task 2, briefly precluding the selection of a Task 2 response. This involves removing "GOAL DO TASK 2" from working memory for a short while. Temporary suspension of Task 2 is a prerequisite for shifting the Task 2 production rules from deferred to immediate response-transmission mode. If Task 2 were not suspended during this shift, then a selected Task 2 response might be put in working memory at the same time as the Task 2 production rules enter immediate mode, and so the selected response might remain in working memory and never reach its motor processor.

As soon as the executive process has suspended Task 2, it next shifts the Task 2 response-transmission mode from deferred to immediate. Here the note "STRATEGY TASK 2 IS DEFERRED" is replaced with the note "STRATEGY TASK 2 IS IMMEDIATE" in working memory. Following the mode shift, Task 2 responses that are selected subsequently will be sent directly to their motor processor after Task 2 is resumed again. In effect, the deferred-to-immediate mode shift helps further promote the completion of Task 2.

Finally, the last substep of the unlocking routine is to resume Task 2. This involves reenabling response selection for Task 2 by putting "GOAL DO TASK 2" back in working memory. Once the executive process has finished Task 2 resumption, the remainder of Task 2 -- in particular, both response selection and movement production -- can proceed directly to completion.

Anticipatory response preparation. After the unlocking routine is done, the executive process may also take one more step: anticipatory preparation of a Task 2 response movement. This occurs if the SOA is long and response selection for Task 2 has not already begun. The preparation involves sending the features of anticipated Task 2 response movements to their motor processor, which then programs them in advance, thereby reducing the time that will be taken for later feature preparation when the motor processor subsequently receives the full identity of the selected Task 2 response. For example, if all of the alternative Task 2 responses require finger presses by the right hand, then the executive process may instruct the manual motor processor to program the right-hand feature without yet knowing which particular finger will ultimately be involved.

Relation to Past Theoretical Proposals

Of course, the SRD model is not entirely new. As should be evident by now, some of its assumptions are similar to ones in past theoretical proposals. We assume that at short SOAs, the selection of Task 2 responses may proceed simultaneously with the selection of Task 1 responses, but that the initiation of overt movements in Task 2 is deferred temporarily. This resembles previous assumptions made under the movement-production bottleneck model (e.g., Kantowitz, 1974; Keele, 1973; Keele & Neill, 1978; Logan & Burkell, 1986; Reynolds, 1964). On the other hand, we assume that at intermediate SOAs, the selection of Task 2 responses is briefly suspended by an executive process, which shifts Task 2 from deferred to immediate response-transmission mode. During this mode shift, the SRD model's internal states would be consistent with the existence of a response-selection bottleneck (e.g., Pashler, 1984, 1990, 1993; Welford, 1952, 1959). A combination of

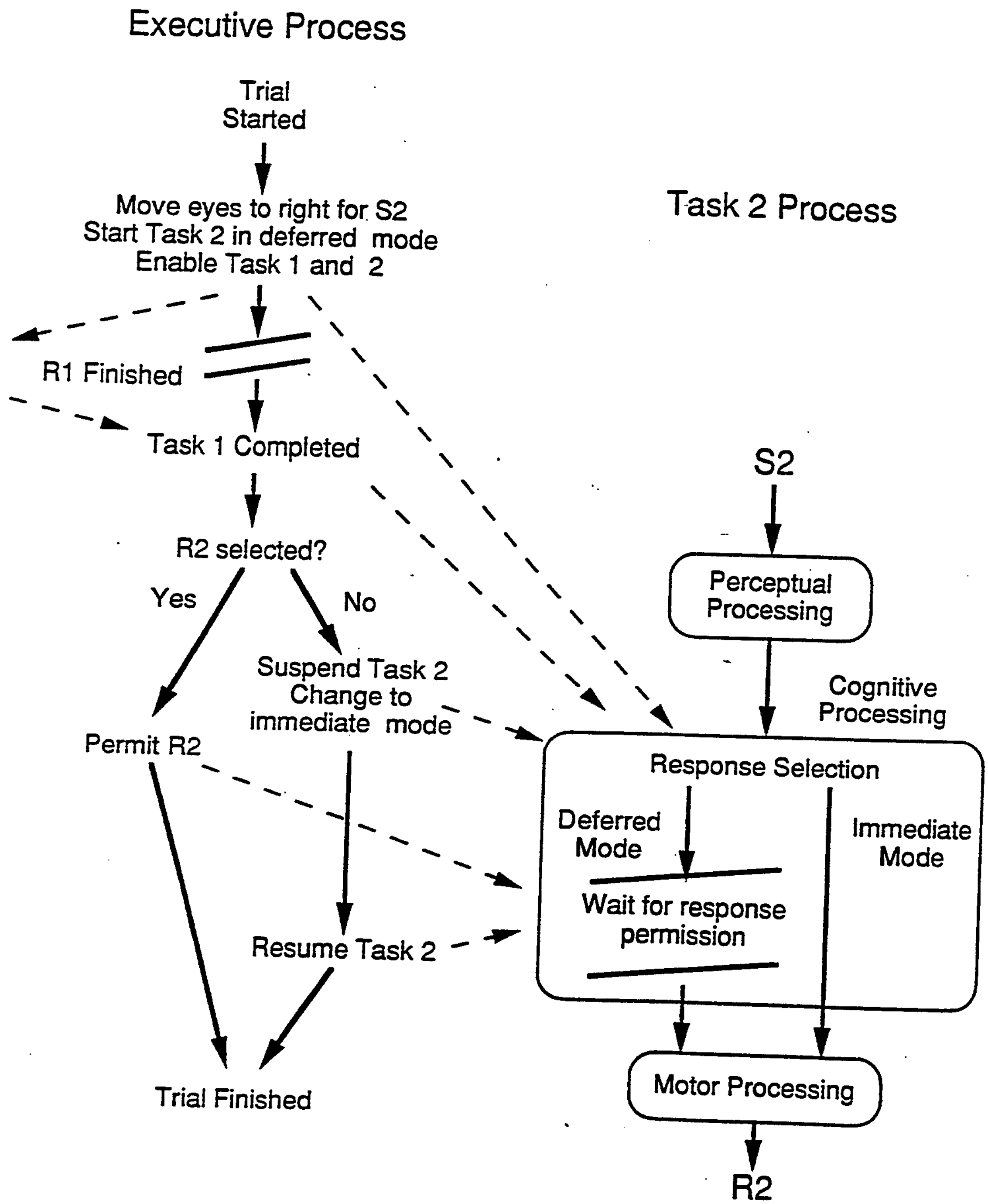

Figure 9. Steps taken by the SRD model's executive process to "unlock" Task 2 of the PRP procedure after Task 1 has been declared "done" (cf. Figure 8). Depending on whether or not a Task 2 response has been selected already, the executive process unlocks Task 2 either by permitting the selected Task 2 response to be sent to its motor processor, or by suspending Task 2 temporarily, shifting it from deferred to immediate response-transmission mode, and then resuming Task 2 in immediate mode. Breaks in the vertical time lines indicated by diagonal hash marks represent variable time intervals whose durations depend on the SOA and the temporal properties of prior processes.

variable time intervals whose durations depend on the SOA and the temporal properties of prior processes.

model, has been proposed by De Jong (1993). Furthermore, the SRD model's executive process also functions somewhat like the allocation policies (Kahneman, 1973), Supervisory Attentional System (Norman & Shallice, 1986), and central controller (Schneider & Detweiler, 1988) introduced by previous theorists.

Nevertheless, there are crucial differences between the SRD model and its predecessors. Unlike other alternatives, the SRD model is based on a cognitive processor with unlimited capacity to test and apply multiple production rules simultaneously. The model's executive process controls the flow of information through temporary programmable bottlenecks; it is not constrained by a permanent hardware bottleneck of the sort assumed in the response-selection bottleneck model. Also, the motor processors that the SRD model uses for different response modalities (e.g., manual and vocal) may function simultaneously; it has no peripheral amodal movement-production bottleneck per se. On the basis of our present theoretical framework, the PRP effect and other related phenomena are instead attributed to strategic partial lockout scheduling and deferred response transmission, which are governed by the SRD model's executive process for satisfying task priorities and avoiding conflicts within the same (e.g., manual) motor processor. The coordinative functions of the present executive process are precisely specified and implemented in computer simulations that yield outputs directly comparable to data from actual experiments, whereas this has not been typically the case yet in other theoretical treatments of supervisory control and resource allocation.

Algebraic Description of Theoretical and Simulated RTs

Because of its unique combination of characteristics, the SRD model has many interesting implications about patterns of RTs in the PRP procedure. Some implications can be derived from simple mathematical analyses, whereas others are best demonstrated by computer simulation. Together, these two approaches -- analysis and simulation -- complement each other nicely for present purposes. Simulations with the SRD model let us verify that its assumptions are well-defined and logically sufficient for describing basic multiple-task performance. The simulation process also yields numerical predictions about theoretical mean RTs that would be difficult or impossible to obtain mathematically. Nevertheless, despite such difficulties, it is possible to formulate some algebraic equations for the mean RTs implied by the SRD model. With these equations, we can estimate appropriate values of some parameters on which the model and its EPIC architecture rely (*Appendix 4*), and we can evaluate the model's goodness-of-fit to empirical data in a principled fashion. Just as important, the theoretical RT equations clarify why simulated RTs exhibit various quantitative patterns, depending on details of the experimental conditions. Thus, through joint analysis and simulation, the SRD model promises to account precisely for RT data from a range of empirical studies.

In subsequent sections, we pursue these prospects more fully through simple mathematical analyses of the SRD model. As part of this pursuit, some parameters associated with the model and its EPIC architecture are introduced next. On their basis, algebraic equations that describe theoretical and simulated RTs for both Tasks 1 and 2 of the PRP procedure will be derived. Then, after these steps, our simulations with the SRD model will be presented.

Architecture and Model Parameters

Table 2 summarizes several types of parameter relevant to the EPIC architecture and SRD model. These parameters include some that modulate the dynamics of EPIC's perceptual, cognitive, and motor processors; they are "built in" the system components and do not depend on the particular sets of production rules used by the SRD model for performing individual tasks. Also included are other parameters that do depend on these rule sets and that emerge from the SRD model's task or

Table 2

Parameters for Simulations with The SRD Model

System Component	Parameter Name	Symbol	Type	Mean	Source
cognitive processor	cycle duration	t_c	S	50	G
	working-memory gating time	t_g	S	25	G
perceptual processors	stimulus detection time	t_d	S	x	G, E
	stimulus identification time	t_i	S	x	G, E
motor processors	number of movement features	n_f	C	2	G
	preparation time per feature	t_f	S	50	G
	action-initiation time	t_a	S	50	G
	movement-production time	t_m	S	150	G
	preparation benefit	t_p	S	x	G
task processes	number of selection cycles	n_s	S	x	G, E
	response-selection time	t_s	S	x	G, E
executive process	ocular-orientation time	t_o	S	x	I
	unlocking-onset latency	t_u	S	x	E
	minimum unlocking duration	t_v	S	100	G
	suspension waiting time	t_w	S	x	I
	preparation waiting time	t_y	S	x	I
apparatus	response-transduction time	t_r	C	x	G, E

Note. For the types of parameter listed above, S = stochastic, and C = constant. Numerical times are given in milliseconds for the means of context-independent parameters, which stay the same across all task conditions; "x" indicates context-dependent parameters whose means change as a function of task conditions. For the sources of the parameter means, G = informal guesstimation; I = iterative simulation; E = formal estimation (see text). Some parameters are linearly or multiplicatively related to others, reducing the total number of independent parameters; in particular, $t_g = 0.5t_c$; $t_m = (n_f \times t_f) + t_a$; and $t_s = n_s \times t_c$.

Although the total number of parameters in Table 2 may seem large, this appearance is deceptive. Many of the SRD model's and EPIC's parameters are linearly or multiplicatively related to each other; we treat them as being distinct here merely for purposes of exposition. Furthermore, the mean numerical values assigned to many of these parameters stay fixed across all of our simulations. Thus, as later sections of the article describe in more detail, the model actually has relatively few adjustable parameters and degrees of freedom with which to account for empirical data.

Cognitive-processor parameters. The most basic parameter associated with EPIC's cognitive processor is the *cycle duration* (t_c). It is the duration of each cycle during which the cognitive processor tests the conditions and executes the actions of production rules in procedural memory. As mentioned before, t_c is unaffected by the number of production rules that have to be processed. However, because individual task and executive processes typically take more than one cycle to be completed, their completion times and resulting RTs depend directly on t_c.

Stemming from the cognitive-processor cycle duration is another parameter, the *working-memory gating time* (t_g). It is the time between the moments when a new item of information (e.g., a stimulus identity) enters working memory and the cognitive processor can first use this item in subsequent operations. On average, t_g equals half of t_c, because the cognitive processor examines the contents of working memory at the start of each cycle, but ignores any further items that enter during the remainder of the cycle.

Perceptual-processor parameters. EPIC's perceptual processors have some additional parameters. One of them is a modality-specific *stimulus detection time* (t_d). It is the time from the external onset of a stimulus until the perceptual processor devoted to its sensory modality puts a detection symbol in working memory, indicating that the stimulus onset has occurred. During simple-reaction tasks, the sum of t_d and t_g determines when response selection and transmission can begin.

A second perceptual-processor parameter is the *stimulus identification time* (t_i). It is the time from the onset of a presented stimulus until the perceptual processor for its modality puts the identity of the stimulus in working memory. During choice-reaction tasks, the sum of t_i and t_g determines when response selection can begin.

Motor-processor parameters. Similarly, several parameters contribute to operations by EPIC's motor processors. They include (1) the *number of movement features*, n_f, prepared by a motor processor when it converts a selected response symbol to an overt movement, (2) the *time per movement feature*, t_f, taken to complete this conversion, and (3) the *action initiation time*, t_a, taken to begin an overt movement after all of its requisite features have been prepared. These parameters combine to yield a *movement-production time* (t_m). By definition, $t_m = (n_f \times t_f) + t_a$, which is the total time that a motor processor takes to transform a selected response into the onset of physical motion, assuming the movement has not already been partially prepared in advance.

Supplementing the movement-production time is the *preparation-benefit time* (t_p). It plays a role when some of the movement features for a response are prepared in advance, before the full identity of the response has been selected and sent to its motor processor. On such occasions, t_p equals a product of the preparation time per feature (i.e., t_f) and number of features prepared in advance. The preparation benefit is then subtracted from the "normal" (unprepared) contribution of the movement-production time to the total RT.

Task-process parameters. For each task process of the SRD model, an important parameter is the *number of response-selection cycles* (n_s) per trial. It equals the total cycles taken by EPIC's cognitive processor in selecting the response to a stimulus, once the stimulus's identity is in working memory and the task's production rules have been enabled. The value of n_s depends on the specific production rules used during response selection, which may change as a function of factors such as S-R compatibility and S-R numerosity.

For now, n_s is crucial because it combines multiplicatively with the cycle duration, t_c, to yield the *response-selection time* (t_s). This product (i.e., $t_s = n_s \times t_c$) is the total time taken by the cognitive processor on each trial for response selection. Thus, t_s depends on a task's production rules, just as n_s does.

Executive-process parameters. Five more parameters are associated with the executive process of the SRD model. The first of these is the *ocular-orientation time* (t_o). It is the time taken from the onset of a Task 1 stimulus until the executive process, using the ocular motor processor, has positioned EPIC's eyes at the spatial location of a visual Task 2 stimulus. Under the SRD model, the value of t_o is set by specifying trigger events that match the conditions of the executive-process production rules whose actions control the ocular motor processor. For example, suppose the Task 1 stimulus is auditory whereas the Task 2 stimulus is visual, and suppose a visual warning signal precedes the Task 1 stimulus. Then detection of the warning signal's onset may trigger an immediate eye movement to the anticipated Task 2 stimulus location before the Task 1 stimulus starts, so t_o would be zero and not contribute to the subsequent Task 2 RT. However, if both the Task 1 and Task 2 stimuli are visual, or if looking at the Task 2 stimulus location is postponed temporarily for other reasons, then t_o could be subtantially greater and dramatically increase the Task 2 RT.

A second executive-process parameter is the *unlocking-onset latency* (t_u). It is the time between two intermediate events: (1) transmission of a selected Task 1 response to its motor processor; (2) initiation of the shift from deferred to immediate response-transmission mode for the Task 2 production rules. The value of t_u is set by specifying what internal state during the production of an overt Task 1 response qualifies Task 1 to be declared "done." This specification may depend on several factors, such as which motor processor is used for performing each task of the PRP procedure, and how conservative the executive process must be to ensure that Task 1 responses always precede Task 2 responses. For example, if both tasks require using EPIC's manual motor processor, then Task 1 may not be declared "done" until the manual motor processor has initiated an overt Task 1 response, so t_u would include the entire movement-production time (i.e., t_m). In contrast, if the two tasks require different motor processors (e.g., manual and vocal), and if some out-of-order responses are tolerated, then Task 1 may be declared "done" as soon as its motor processor signals receipt of the Task 1 response identity, so t_u could be much shorter.

A third executive-process parameter is the *minimum unlocking duration* (t_v). Its value is set by specifying the production rules that unlock Task 2 after Task 1 has been declared "done." If the Task 2 response has been selected already and put in working memory through the deferred response-transmission mode, then t_v is the time between the respective moments when Task 1 is declared to be "done" and the identity code for the selected Task 2 response reaches its motor processor. Alternatively, if the Task 2 response has not been put in working memory before Task 1 is "done," then t_v is the time taken by the executive process to suspend Task 2 temporarily and shift it from deferred to immediate response-transmission mode (cf. Figure 9).

A fourth executive-process parameter is the *suspension waiting time* (t_w). It is an extra amount of time during which the executive process keeps Task 2 suspended after the deferred-to-immediate mode shift has been completed. The value of t_w is set by specifying how many additional cognitive-processor cycles the executive process waits during this period. In some cases, this specification can help avoid out-of-order responses, and it also accounts for interesting details of PRP curves that are otherwise difficult to explain.

A fifth executive-process parameter is the *preparation waiting time*, t_y . It is an amount of time that the executive process waits before starting anticipatory preparation of Task 2 movement features after the Task 1 response movement has been initiated. The value of t_y is set by specifying an event that triggers a production rule to start anticipatory movement-feature preparation during Task 2. For example, this event might correspond to EPIC's tactile perceptual processor detecting the end of the overt Task 1 response and putting a corresponding detection symbol in working memory. In turn, t_y would then depend on the tactile detection time. More generally, the length of t_y may be inversely related to the amount of emphasis placed on completing Task 2 quickly at long SOAs.

Apparatus parameters. Finally, because we seek to mimic subjects' measured performance as closely as possible, the SRD model has an apparatus parameter, the *response-transduction time* (t_r). It is an extra amount of time between the respective moments when an overt response movement begins and a movement-recording device would transduce the movement's physical onset. This time presumably depends on the response modality and recording device that are involved, thereby influencing predicted and observed RTs. For example, vocal RTs may involve greater values of t_r than manual RTs do, because the onsets of audible vocal sounds recorded with a voice key are often delayed substantially (e.g, on the order of 100 ms or more) relative to the onsets of the articulatory movements that produce them, whereas manual keypresses can trigger corresponding switch closures almost instantaneously (e.g., on the order of 10 ms or less).

Task 1 RT Equation

On the basis of the preceding parameters, some equations can be formulated to characterize theoretical RTs. According to the SRD model, Task 1 of the PRP procedure receives highest priority, and performance of it progresses from start to finish in the same rapid fashion regardless of the stimulus-onset asynchrony (SOA) between the Task 1 and Task 2 stimuli. The model assumes that Task 1 entails a sequence of stages, which start at the onset of the Task 1 stimulus and include the following steps: (1) detection and, if need be, identification of the Task 1 stimulus by a perceptual processor; (2) selection of a Task 1 response by the cognitive processor, and transmission of the response's identity to its motor processor; (3) preparation of movement features and initiation of action by the motor processor; and (4) transduction of the response movement. Thus, when two or more alternative S-R pairs are involved, the theoretical Task 1 RT on each trial of the PRP procedure is

$$RT_1 = t_{i1} + t_g + t_{s1} + t_{m1} + t_{r1} \,. \tag{1}$$

Here t_{i1} is the Task 1 stimulus-identification time; t_g is the working-memory gating time; t_{s1} is the Task 1 response-selection time; t_{m1} is the Task 1 movement-production time; and t_{r1} is the Task 1 response-transduction time. When Task 1 involves simple reactions (i.e., only one possible S-R pair) instead of choice reactions, the stimulus identification time (t_{i1}) would be replaced by the stimulus detection time (t_{d1}) in Equation 1.

Given this equation, which has additive contributions from EPIC's component processors to the Task 1 RT, it is apparent that the SRD model involves discrete serial stages of processing (Meyer, Irwin, Osman, & Kounios, 1988b; Meyer et al., 1988c; Miller, 1988; Sternberg, 1969). Some theorists who have espoused continuous parallel information processing (e.g., McClelland, 1979; Rumelhart & McClelland, 1986) might therefore argue that our treatment of multiple-task performance is too simplistic. Still, there is at least some a priori empirical justification for adopting discrete stage models here. In many cases, the temporal properties of observed RT distributions are consistent with an assumption of discrete serial stages (e.g., Meyer et al., 1984, 1985, 1988b, 1988c; Roberts & Sternberg, 1993; Sternberg, 1969). Also, characterizing RTs as additive combinations of time increments has another practical advantage; it facilitates the estimation of parameter values for the SRD model.

Several further aspects of Equation 1 should be mentioned as well. According to it, Task 1 RTs are independent of the SOA and Task 2 response-selection difficulty. Consistent with typical instructions for the PRP procedure, this independence occurs because the executive process of the SRD model always gives highest priority to Task 1. Such prioritization is what subjects usually do too. As we demonstrate later, Task 1 RTs obtained from simulations with the SRD model account well for data from a variety of empirical studies. Furthermore, when empirical Task 1 RTs do depend on the SOA (e.g., Kantowitz, 1974; McLeod, 1978a), the model's executive process -- which can use alternative task-scheduling strategies -- may be modified in a principled fashion to interpret and predict systematic SOA effects. The model's executive process can also mediate effects of Task 2 difficulty on Task 1 RTs, which have been reported previously under some conditions (Kantowitz, 1974; McLeod, 1978a).

Task 2 RT Equations

Unlike for Task 1 RTs, the SRD model implies that Task 2 RTs embody effects of both the SOA and Task 2 response-selection difficulty. The expected pattern stems from properties of the model's executive process. Because of how the executive process works, performance of Task 2 presumably involves a dynamic switching network whose properties generalize those of static Program Evaluation and Review Technique (PERT) networks (e.g., see Fisher & Goldstein, 1983; John, 1988, 1990; Schweickert, 1980; Schweickert & Boggs, 1984; Schweickert & Townsend, 1989).[16]

In particular, five alternative paths of processing may lead from Task 2 stimuli to Task 2 responses under the SRD model. Figures 10 through 13 illustrate four of these paths, which stem from the executive-process operations diagrammed previously (Figures 8 and 9). The path that is actually taken during an individual trial depends on the SOA, the stimulus-identification times, and the response-selection times in Tasks 1 and 2. For each possible path, a distinct equation characterizes the theoretical Task 2 RT as a function of the SRD model's parameters and SOA. The SOA is especially important here because it determines whether the difficulty of response selection in Task 2 contributes additively or interactively to the Task 2 RT.

The next subsections discuss the Task 2 RT equations. A summary of them appears in Table 3. Readers who want to skip the following detailed discussion may consult this table and then proceed directly to the next main section entitled *Theoretical PRP Curves*.

Path 1: RT for Task 2 with post-selection slack. The time line of mental and physical events that happen when Path 1 of information processing is taken during Task 2 appears in Figure 10. In order for these events to occur as shown, the SOA must be "very short" and satisfy the following constraint defined by the parameters of the SRD model:

$$\mathrm{SOA} \leq t_{i1} + t_{s1} + t_u - \max(0, t_{o2} - \mathrm{SOA}) - t_{i2} - t_{s2}\,. \tag{2}$$

Here t_{i1} and t_{s1} are again respectively the Task 1 stimulus-identification and response-selection times; t_u is the unlocking-onset latency of the executive process; t_{o2} is the ocular-orientation time for focusing on the Task 2 stimulus if it is visual; t_{i2} and t_{s2} are respectively the Task 2 stimulus-identification and response-selection times (see Table 2). On the basis of these parameters, the probability of taking Path 1 during Task 2 is a function of the SOA and can be expressed as

$$P(\text{Path } 1 \mid \mathrm{SOA}) = P[\mathrm{SOA} \leq t_{i1} + t_{s1} + t_u - \max(0, t_{o2} - \mathrm{SOA}) - t_{i2} - t_{s2}\,], \tag{3}$$

where Inequality 2 forms the argument on the right side of this equation.

Given Inequality 2, the Task 2 stimulus occurs sufficiently early that the Task 2 response is selected in deferred mode and sent to working memory before the executive process starts unlocking Task 2 (see Figure 10).[17] Further progress on Task 2 therefore has to wait until Task 1 is declared "done" and the executive process finishes unlocking Task 2, which permits the selected Task 2 response to be sent from working memory to its motor processor for movement preparation and overt action. Consequently, taking Path 1 of processing introduces *post-selection slack* (i.e., a pause after response selection) within Task 2. The post-selection slack is the difference between the amounts of time taken to select the Task 2 response and to unlock Task 2, measured from the onset of the Task 1 stimulus (i.e., post-selection slack = $t_{i1} + t_{s1} + t_u + t_v - t_{i2} - t_{s2}$ - SOA, where t_v is the minimum unlocking duration of the executive process, and the other parameters are as before).

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[16] In static PERT networks, processing proceeds simultaneously along two or more distinct paths, and the time to produce an overt output depends on which path requires the most time to be completed; the structure of the network does not change dynamically within or between trials. On the other hand, under the SRD model, only one path of processing is taken for Task 2 during each simulated test trial; the selection of this path stems from contingent switching operations (e.g., temporary suspension and resumption of Task 2 response selection) that coordinate Tasks 1 and 2 dynamically. Across trials, the set of possible paths from stimuli to responses may change, depending on the SOA and other parameter values.

[17] This obtains because measured from the onset of the Task 1 stimulus, the total time until the executive process starts unlocking Task 2 is $t_{i1} + t_g + t_{s1} + t_u$, and the total time until the Task 2 response has been selected in the deferred mode is $\max(\mathrm{SOA}, t_{o2}) + t_{i2} + t_g + t_{s2}$. Inequality 2 makes the latter sum be less than or equal the former, ensuring that Task 2 response selection finishes before Task 2 unlocking begins.

Table 3

Task 2 Reaction Times and Constraints on SOA for The Five Alternative Paths of Processing in Task 2 under the SRD Model

Path	Key Characteristic	Task 2 Reaction Time [RT$_2$(SOA | Path i)]	SOA Constraint
1	post-selection slack	$t_{i1} + t_g + t_{s1} + t_u + t_v + t_{m2} + t_{r2}$ - SOA	SOA $\leq t_{i1} + t_{s1} + t_u$ - max(0, t_{o2} - SOA) - $t_{i2} - t_{s2}$
2	mid-selection slack	max(0, t_{o2} - SOA) $+t_{i2} +t_g +t_{s2} +t_v +t_w +t_{m2} +t_{r2}$	$t_{i1} + t_{s1} + t_u$ - max(0, t_{o2} - SOA) - $t_{i2} - t_{s2} <$ SOA $\leq$ $t_{i1} + t_{s1} + t_u$ - max(0, t_{o2} - SOA) - t_{i2}
3	pre-selection slack	$t_{i1} + t_g + t_{s1} + t_u + t_v + t_w + t_{s2} + t_{m2} + t_{r2}$ - SOA	$t_{i1} + t_{s1} + t_u$ - max(0, t_{o2} - SOA) - $t_{i2} <$ SOA $\leq$ $t_{i1} + t_{s1} + t_u + t_v + t_w$ - max(0, t_{o2} - SOA) - t_{i2}
4	"neutral" baseline	max(0, t_{o2} - SOA) + $t_{i2} + t_g + t_{s2} + t_{m2} + t_{r2}$	$t_{i1} + t_{s1} + t_u + t_v + t_w$ - max(0, t_{o2} - *SOA*) - $t_{i2} <$ SOA $\leq$ $t_{i1} + t_{s1} + t_{m1} + t_y$ - max(0, t_{o2} - SOA) - $t_{i2} - t_{s2}$
5	motor preparation	max(0, t_{o2} - SOA) + $t_{i2} + t_g + t_{s2} + t_{m2} - t_{p2} + t_{r2}$	SOA $> t_{i1} + t_{s1} + t_{m1} + t_y$ - max(0, t_{o2} - SOA) - $t_{i2} - t_{s2}$

Note. For Paths 1 through 5, the above reaction times come respectively from Equations 4, 7, 10, 13, and 16 in the text; correspondingly, the SOA constraints come from Inequalities 2, 5, 8, 11, and 14. The key characteristics outlined above refer to important RT components for each path of processing in Task 2.

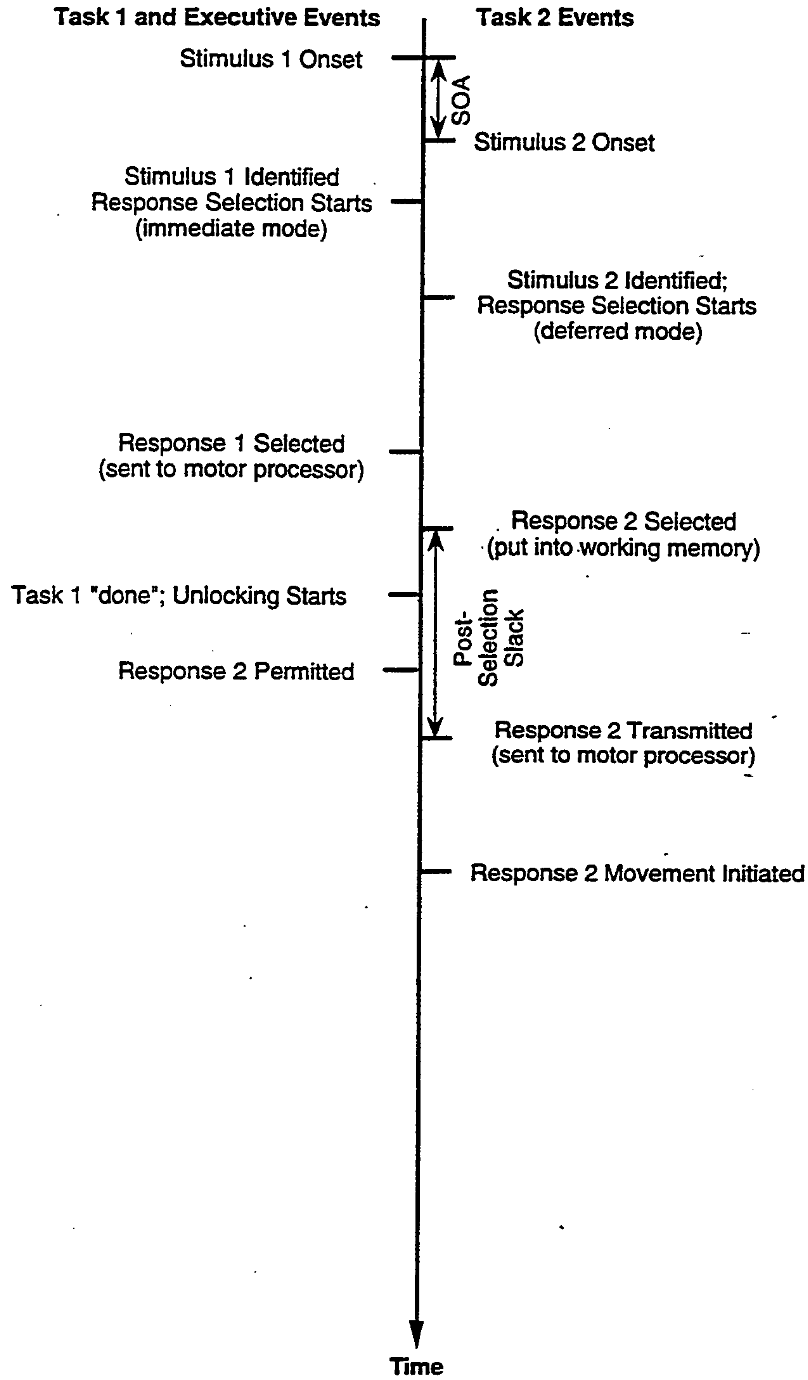

Figure 10. Sequence of mental and physical events implied by the SRD model when the SOA is "very short" and Path 1 of processing is taken for Task 2 of the PRP procedure. Here the SOA must satisfy the Path 1 constraint in Table 3 (cf. Inequality 2 in text), and so the Task 2 RT contains post-selection slack. Parameters spaced along the vertical time line denote durations of the model's component processes (cf. Table 2).

When there is post-selection slack, the Task 2 ocular-orientation, stimulus-identification, and response-selection times do not contribute to the Task 2 RT; the slack absorbs them (Figures 5 and 10). Instead, the Task 2 RT includes additive contributions from several other sources: the time that the SRD model's executive process takes to finish unlocking Task 2, measured from the onset of the Task 1 stimulus ($t_{i1} + t_g + t_{s1} + t_u + t_v$); the Task 2 movement-production time (t_{m2}); and the Task 2 response-transduction time (t_{r2}). Combining these contributions and subtracting the SOA, which must be done because the SOA attenuates the post-selection slack, yields an equation for the RT along Path 1 in Task 2:

$$\mathrm{RT}_2(\mathrm{SOA} \mid \text{Path 1}) = t_{i1} + t_g + t_{s1} + t_u + t_v + t_{m2} + t_{r2} - \mathrm{SOA}\,. \tag{4}$$

Equation 4 has some interesting consequences. Because it omits the Task 2 response-selection time (t_{s2}), the difficulty of response selection (e.g., S-R incompatibility and S-R numerosity) in Task 2 may not affect Task 2 RTs at "very short" SOAs under the SRD model; such effects can be hidden by the post-selection slack. Similarly, post-selection slack can hide contributions from the ocular-orientation time (t_{o2}), which does not appear in Equation 4 either.

However, if the SRD model is correct, then post-selection slack within Task 2 may sometimes be hard to detect empirically. For example, suppose that SOA ≥ 0, as in most experiments with the PRP procedure (e.g., McCann & Johnston, 1992; Pashler, 1984, 1989, 1993; Pashler & Johnston, 1989). Also, suppose that an experiment has been designed such that the sum of the times for Task 1 stimulus identification, response selection, and unlocking onset (i.e., $t_{i1} + t_{s1} + t_u$) is less than the sum of the times for Task 2 stimulus identification and response selection (i.e., $t_{i2} + t_{s2}$). Then Inequality 2 would not be satisfied, so Path 1 would not be taken during Task 2. Indeed, choosing a Task 1 for which stimulus identification and response selection are relatively easy, or choosing a Task 2 for which they are relatively difficult, can preclude post-selection slack in Task 2 even with a zero SOA. In turn, this would make it impossible to discover temporal overlap of the response-selection processes for the two tasks. Such impediments may likewise arise when the ocular-orientation time is relatively long (i.e., $t_{o2} > t_{i1} + t_{s1} + t_u - t_{i2} - t_{s2}$), which can happen with two tasks that involve spatially separate visual stimuli. These considerations perhaps explain why some previous investigators have failed to find post-selection slack and temporal overlap of response-selection processes (e.g., Becker, 1976; Dutta & Walker, 1995; Fagot & Pashler, 1993; McCann & Johnston, 1992; Pashler, 1984, 1989; Pashler & Johnston, 1989; Ruthruff, Miller, & Lachmann, 1995; Schweickert, Dutta, Sangsup, & Proctor, 1992; Van Selst & Jolicoeur, 1993).

Path 2: RT for Task 2 with mid-selection slack. Under the SRD model, information processing may take a second path during Task 2 when the SOA is "moderately short" rather than "very short". The time line of mental and physical events along Path 2 appears in Figure 11. In order for these events to occur as shown, the SOA must satisfy the following constraint:

$$t_{i1} + t_{s1} + t_u - \max(0, t_{o2} - \mathrm{SOA}) - t_{i2} - t_{s2} < \mathrm{SOA} \leq t_{i1} + t_{s1} + t_u - \max(0, t_{o2} - \mathrm{SOA}) - t_{i2}\,. \tag{5}$$

The probability of taking Path 2 during Task 2 is therefore a function of the SOA and SRD model's parameters that can be expressed as

$$\mathrm{P}(\text{Path 2} \mid \mathrm{SOA}) = \mathrm{P}[t_{i1} + t_{s1} + t_u - \max(0, t_{o2} - \mathrm{SOA}) - t_{i2} - t_{s2} < \mathrm{SOA} \leq t_{i1} + t_{s1} + t_u - \max(0, t_{o2} - \mathrm{SOA}) - t_{i2}]. \tag{6}$$

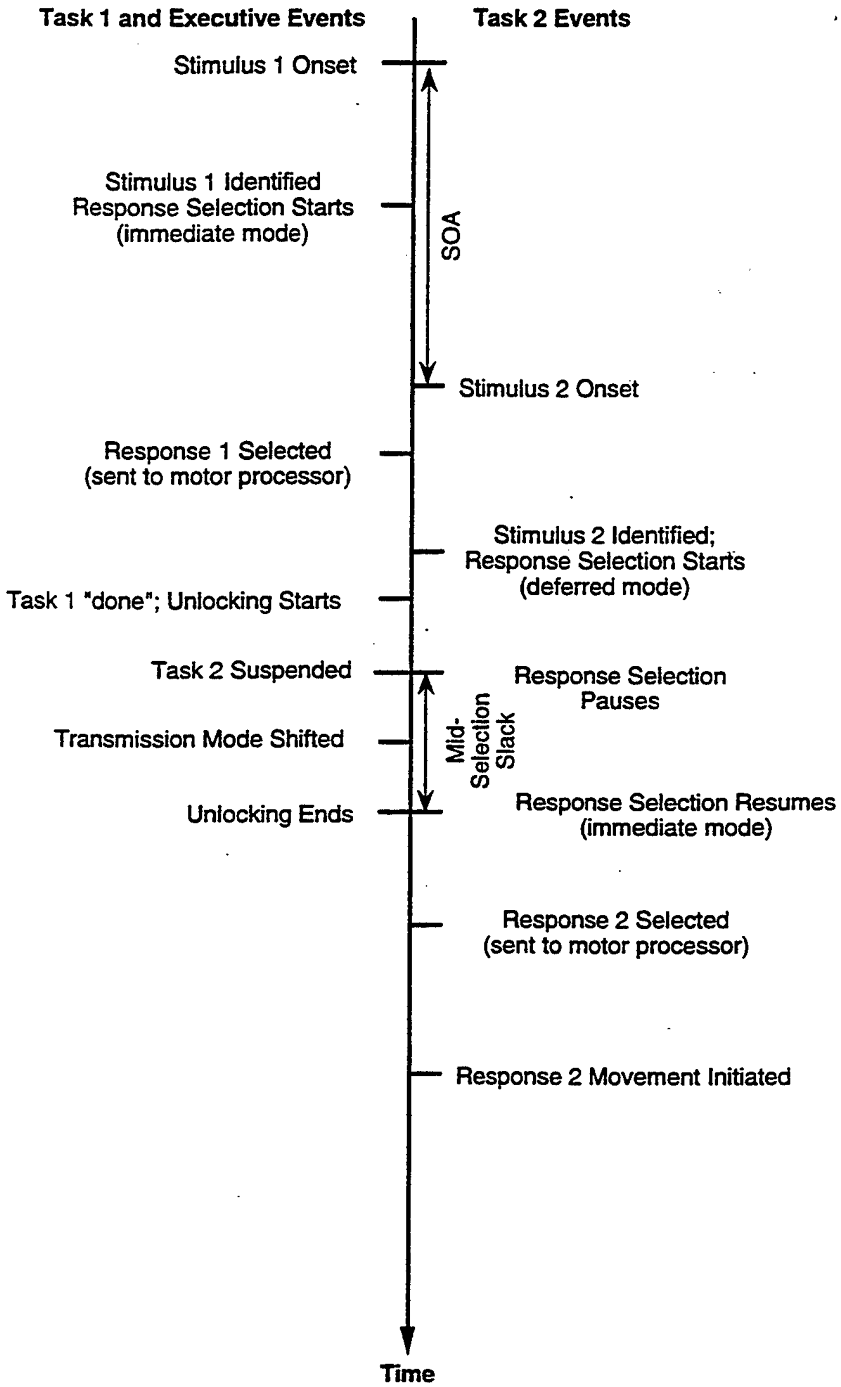

Figure 11. Sequence of mental and physical events implied by the SRD model when the SOA is "moderately short" and Path 2 of processing is taken for Task 2 of the PRP procedure. Here the SOA must satisfy the Path 2 constraint in Table 3 (cf. Inequality 5 in text), and so the Task 2 RT contains mid-selection slack.

Given the right side of Inequality 5, response selection for Task 2 again starts in deferred mode before Task 1 is declared "done" and the executive process unlocks Task 2.[18] However, given the left side of Inequality 5 -- whose terms are the same as those on the right side of Inequality 2 -- Task 2 response selection does not finish until after the executive process has suspended Task 2, shifted it to immediate mode, and completed the unlocking phase (cf. Footnote 16). Consequently, taking Path 2 introduces *mid-selection slack* (i.e., a pause during response selection) within Task 2. The mid-selection slack is the time that Task 2 response selection stays suspended while the unlocking phase is being completed (i.e., mid-selection slack = $t_v + t_w$, where t_v is the minimum unlocking duration, and t_w is additional suspension waiting time).

When there is mid-selection slack, several components contribute additively to the Task 2 RT (Figure 11). These include the times taken to fixate and identify the Task 2 stimulus, start and progress part way through selecting a Task 2 response, unlock Task 2, finish selecting the Task 2 response, produce the response movement, and transduce the overt response. Thus, the Task 2 RT obtained from Path 2 after a specified SOA is

$$RT_2(SOA \mid \text{Path } 2) = \max(0, t_{o2} - SOA) + t_{i2} + t_g + t_{s2} + t_v + t_w + t_{m2} + t_{r2}. \tag{7}$$

Among the terms in Equation 7, a salient one is $\max(0, t_{o2} - SOA)$, which embodies the only contribution of the SOA to the RT in Task 2 when Path 2 is taken. Because a "max" transformation applies here, the SOA's contribution will equal zero whenever $SOA \geq t_{o2}$. Under such circumstances, the SRD model implies -- suprisingly -- that Task 2 RTs are independent of the SOA. This implication stems from how the model's executive process works. When Path 2 is taken, the SOA does not influence how long Task 2 response selection remains suspended after it has begun; the suspension always lasts a total time equal to $t_v + t_w$, the sum of the minimum unlocking duration and suspension waiting time. As the SOA increases, portions of the selection process are merely transferred from before the moment of Task 2 suspension to after the moment of Task 2 resumption, so the magnitudes of the mid-selection slack and the Task 2 RT stay the same.

Indeed, according to the SRD model, Task 2 RTs may exhibit an even more extreme form of non-monotonicity as a function of the SOA, because Equation 7 also contains t_w, the suspension waiting time. If t_w is relatively large, then the Task 2 RTs after "moderately short" SOAs that lead to Path 2 can exceed those after "very short" SOAs that lead to Path 1 (cf. Equation 4). This implication is consistent with some intriguing results from early PRP studies (Welford, 1959). In contrast, however, those results cast doubt on a simple response-selection bottleneck model, which implies that Task 2 RTs should decrease monotonically as the SOA increases (Pashler, 1984, 1990, 1993; Smith, 1967; Welford, 1967).[19]

Another important term in Equation 7 is t_{s2}, the Task 2 response-selection time. Through it, the difficulty of selecting a Task 2 response contributes additively to Task 2 RTs when Path 2 is taken. Such additivity will occur even though, under these circumstances, there is some temporal overlap of the response-selection processes for Tasks 1 and 2 before the mid-selection slack in Task 2 begins (Figure 11). Contrary to inferences made by some investigators (e.g., Becker, 1976; Dutta &

[18] This obtains because measured from the onset of the Task 1 stimulus, the time taken for Task 2 response selection to begin is $SOA + \max(0, t_{o2} - SOA) + t_{i2} + t_g$, whereas the time taken for Task 1 to be declared "done" and unlocking of Task 2 to begin is $t_{i1} + t_g + t_{s1} + t_u$. Task 2 response selection will therefore start before unlocking does if, and only if, $SOA + \max(0, t_{o2} - SOA) + t_{i2} \leq t_{i1} + t_{s1} + t_u$. The latter constraint is equivalent to the right side of Inequality 5.

[19] According to Welford (1959) and some other researchers, Task 2 RTs that do not decrease monotonically with increasing SOAs may stem from disruptions caused by tactile feedback after the Task 1 response. Supposedly, such feedback can enter a single-channel mechanism and preempt processing of the Task 2 stimulus at intermediate SOAs. In some respects, Equation 7 agrees with this conjecture. Nevertheless, there are also crucial differences here. We attribute non-monotonicity of Task 2 RTs to a temporary suspension of response selection while the executive process unlocks Task 2; in the SRD model, this suspension may occur well before tactile feedback from the Task 1 response reaches working memory. The model's executive process may start unlocking Task 2 as early as when the Task 1 motor processor receives its input, hundreds of milliseconds ahead of subsequent tactile feedback.

Walker, 1995; Fagot & Pashler, 1993; McCann & Johnston, 1992; Pashler, 1984, 1989, 1993; Pashler & Johnston, 1989; Ruthruff, Miller, & Lachmann, 1995; Schweickert et al., 1992; Van Selst & Jolicoeur, 1993), additive effects of response-selection difficulty on Task 2 RTs at "moderately short" SOAs do not necessarily prove that response-selection processes for Tasks 1 and 2 are completely separated in time.

Path 3: RT for Task 2 with pre-selection slack. A third path between Task 2 stimuli and responses may be taken when the SOA is "intermediate" rather than "very short" or "moderately short." The time line of mental and physical events along Path 3 appears in Figure 12. In order for these events to occur as shown, the SOA must satisfy the following contraint:

$$t_{i1} + t_{s1} + t_u - \max(0, t_{o2} - \text{SOA}) - t_{i2} < \text{SOA} \leq t_{i1} + t_{s1} + t_u + t_v + t_w - \max(0, t_{o2} - \text{SOA}) - t_{i2}\,. \qquad (8)$$

The probability of taking Path 3 during Task 2 is therefore

$$\text{P(Path 3|SOA)=P}[t_{i1}+t_{s1}+t_u-\max(0,t_{o2}-\text{SOA})-t_{i2} < \text{SOA} \leq t_{i1}+t_{s1}+t_u+t_v+t_w-\max(0,t_{o2}-\text{SOA})-t_{i2}]. \quad (9)$$

Given the right side of Inequality 8, the Task 2 stimulus is identified and put in working memory before the SRD model's executive process has finished unlocking Task 2 and resumed it in immediate mode.[20] However, given the left side of Inequality 8 -- whose terms are the same as those on the right side of Inequality 5 -- response selection for Task 2 does not start until after the unlocking and resumption of Task 2 have been completed (cf. Footnote 17). Consequently, taking Path 3 introduces *pre-selection slack* (i.e., a pause before response selection starts) within Task 2. The pre-selection slack is the difference between the amounts of time taken to identify the Task 2 stimulus and to unlock Task 2 in immediate mode, measured from the onset of the Task 1 stimulus (i.e., pre-selection slack = $t_{i1} + t_{s1} + t_u + t_v + t_w - \max(0, t_{o2} - \text{SOA}) - t_{i2} - \text{SOA}$).

When there is pre-selection slack, the Task 2 ocular-orientation and stimulus-identification times do not contribute to the Task 2 RT; the slack aborbs them (Figure 12). Instead, the Task 2 RT includes additive contributions from several other sources: the time that the SRD model's executive process takes to unlock Task 2 in immediate mode, measured from the onset of the Task 1 stimulus; the Task 2 response-selection time; the Task 2 movement-production time; and the Task 2 response-transduction time. Combining these contributions and subtracting the SOA, which must be done because the SOA reduces the pre-selection slack, yields an equation for the RT along Path 3 in Task 2:

$$\text{RT}_2(\text{SOA} \mid \text{Path 3}) = t_{i1} + t_g + t_{s1} + t_u + t_v + t_w + t_{s2} + t_{m2} + t_{r2} - \text{SOA}\,. \qquad (10)$$

Unlike the previous RT equations, this one contains separate contributions from both the SOA and Task 2 response-selection time (t_{s2}). Thus, when Path 3 is taken, the SRD model implies that the SOA and response-selection difficulty in Task 2 affect the Task 2 RT additively. Despite conclusions reached by some previous investigators (Becker, 1976; Dutta & Walker, 1995; Fagot & Pashler, 1993; McCann & Johnston, 1992; Pashler, 1984, 1989, 1993; Pashler & Johnston, 1989; Ruthruff, Miller, & Lachmann, 1995; Schweickert et al., 1992; Van Selst & Jolicoeur, 1993), such additivity does not strongly support a simple response-selection bottleneck model over other alternatives, and instead may stem from a model that has no immutable central bottlenecks.

Path 4: RT for Task 2 at "neutral" baseline. If the SOA is "moderately long" rather than "intermediate," then a fourth path from Task 2 stimuli to responses may be taken instead of Path 3. The time line of mental and physical events along Path 4 appears in Figure 13. In order for these events to occur as shown, the SOA must satisfy the following constraint:

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[20] This obtains because measured from the onset of the Task 1 stimulus, the time taken to identify the Task 2 stimulus and put it in working memory is SOA + $\max(0, t_{o2} - \text{SOA}) + t_{i2} + t_g$, whereas the time taken to finish unlocking Task 2 and resume it in immediate mode is $t_{i1} + t_g + t_{s1} + t_u + t_v + t_w$. The right side of Inequality 8 constrains the former sum to be less than or equal the latter.

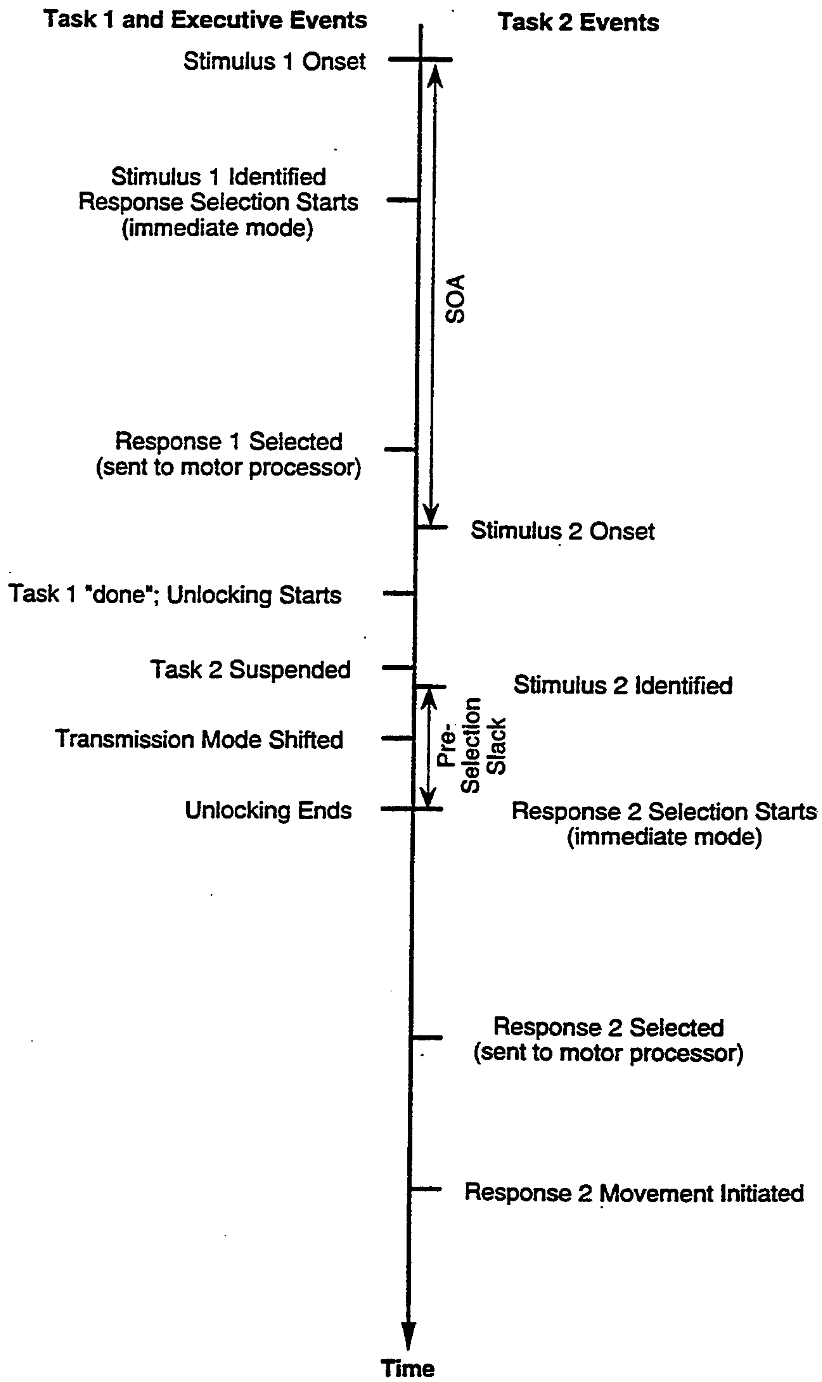

Figure 12. Sequence of mental and physical events implied by the SRD model when the SOA is "intermediate" and Path 3 of processing is taken for Task 2 of the PRP procedure. Here the SOA must satisfy the Path 3 constraint in Table 3 (cf. Inequality 8 in text), and so the Task 2 RT contains pre-selection slack.

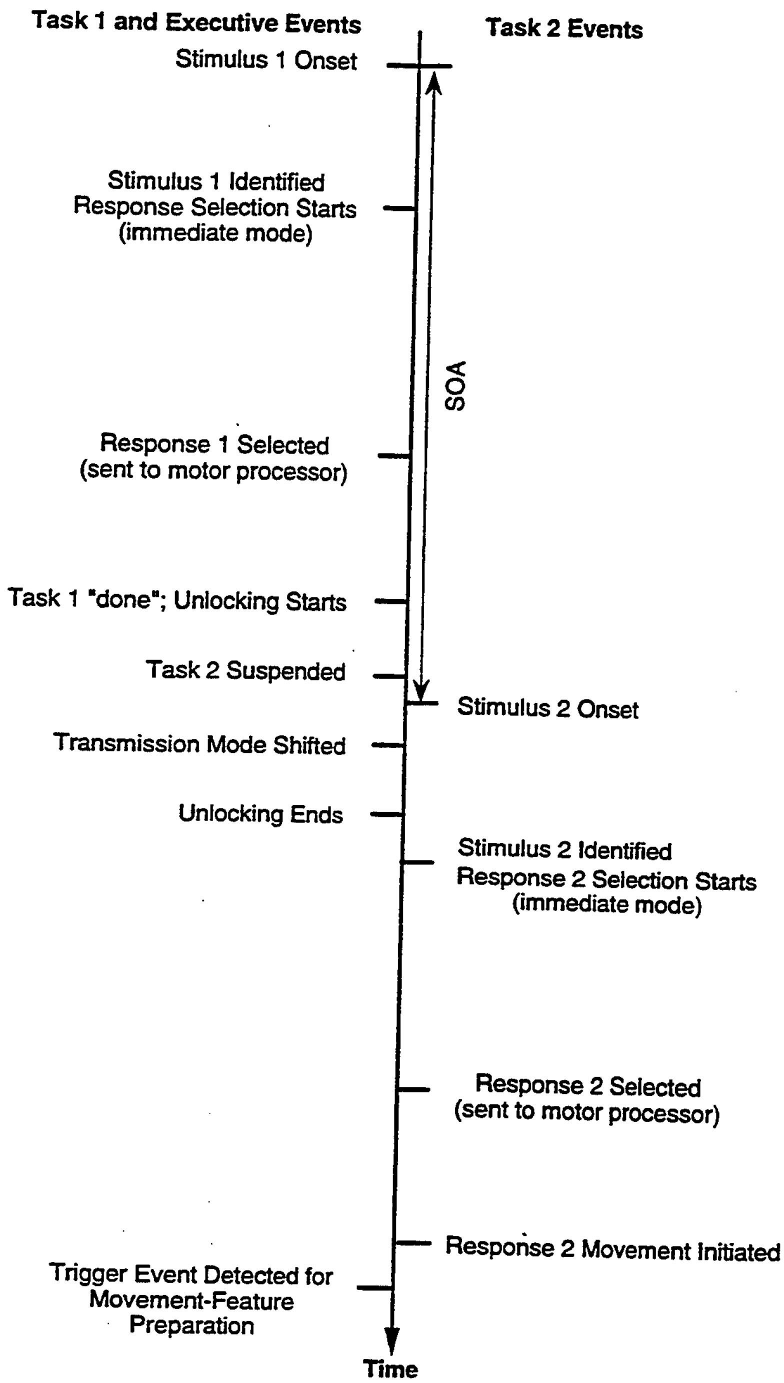

Figure 13. Sequence of mental and physical events implied by the SRD model when the SOA is "moderately long" and Path 4 of processing is taken for Task 2 of the PRP procedure. Here the SOA must satisfy the Path 4 constraint in Table 3 (cf. Inequality 11 in text), and so the Task 2 RT constitutes a neutral baseline, containing neither slack nor preparation benefit.

$$t_{i1}+t_{s1}+t_u+t_v+t_w-\max(0, t_{o2}-\text{SOA})-t_{i2} < \text{SOA} \leq t_{i1}+t_{s1}+t_{m1}+t_y-\max(0, t_{o2}-\text{SOA})-t_{i2}-t_{s2}. \quad (11)$$

The probability of taking Path 4 during Task 2 is therefore

$$P(\text{Path 4}|\text{SOA})=P[t_{i1}+t_{s1}+t_u+t_v+t_w-\max(0,t_{o2}-\text{SOA})-t_{i2}<\text{SOA} \leq t_{i1}+t_{s1}+t_{m1}+t_y-\max(0,t_{o2}-\text{SOA})-t_{i2}-t_{s2}]. \quad (12)$$

Given the left side of Inequality 11, whose terms are the same as those on the right side of Inequality 8, identification of the Task 2 stimulus is not completed until after the executive process finishes unlocking and resuming Task 2 in immediate mode (cf. Footnote 19). As a result, no slack occurs within Task 2 when Path 4 is taken, because no Task 2 processes have to pause before, during, or after Task 2 response selection.[21] However, given the right side of Inequality 11, which includes the preparation-waiting time (t_y), no movement features are prepared in advance for the Task 2 response before it is selected and sent to its motor processor for movement production.[22]

Under these circumstances, we may express the RT in Task 2 as simply a sum of the times taken for stimulus identification, working-memory gating, response selection, movement production, and response transduction. Thus, the Task 2 RT obtained from Path 4 after a specified SOA is

$$RT_2(\text{SOA} \mid \text{Path 4}) = \max(0, t_{o2} - \text{SOA}) + t_{i2} + t_g + t_{s2} + t_{m2} + t_{r2}. \quad (13)$$

Assuming that the ocular-orientation time is relatively short ($t_{o2} \leq$ SOA), Equation 13 defines a "neutral" baseline for the Task 2 RTs, which can help us later to estimate relevant parameter values.

Path 5: RT for Task 2 with anticipatory movement preparation. Lastly, when the SOA is "very long," a fifth path of processing may be taken in Task 2. For this to occur, the SOA must satisfy the following contraint:

$$\text{SOA} > t_{i1} + t_{s1} + t_{m1} + t_y - \max(0, t_{o2} - \text{SOA}) - t_{i2} - t_{s2}. \quad (14)$$

The probability of taking Path 5 during Task 2 is therefore

$$P(\text{Path 5} \mid \text{SOA}) = P[\text{SOA} > t_{i1} + t_{s1} + t_{m1} + t_y - \max(0, t_{o2} - \text{SOA}) - t_{i2} - t_{s2}]. \quad (15)$$

Given Inequality 14, whose terms are the same as those on the right side of Inequality 11, some movement features can be prepared in advance for Task 2 before the selection of its response is finished (cf. Footnote 21). As a result, the Task 2 RT then drops below the "neutral" baseline of Equation 13 by an amount equal to the preparation-benefit time (t_{p2}), which reduces the time spent on movement-feature preparation after the selected Task 2 response goes to its motor processor for final output. This yields

$$RT_2(\text{SOA} \mid \text{Path 5}) = \max(0, t_{o2} - \text{SOA}) + t_{i2} + t_g + t_{s2} + t_{m2} - t_{p2} + t_{r2}. \quad (16)$$

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21 Note that as mentioned earlier, EPIC's perceptual processors operate in parallel with other system components, so even when Task 2 has been suspended at the level of the cognitive processor, stimulus identification for Task 2 proceeds simultaneously with Task 1 and the executive processes.

22 By definition, the preparation-waiting time is the time that the executive process waits after initiation of the overt Task 1 response before preparing any movement features anticipatorily for the Task 2 response. Measured from the onset of the Task 1 stimulus, the total time before the executive process may start anticipatory movement-feature preparation for Task 2 is $t_{i1} + t_g + t_{s1} + t_{m1} + t_y$, whereas the total time until an appropriate motor processor receives the identity of the selected Task 2 response is SOA + $\max(0, t_{o2} - \text{SOA}) + t_{i2} + t_g + t_{s2}$. The latter sum is greater than or equal the former if, and only if, the right side of Inequality 11 holds.

The right side of Equation 16 constitutes the fastest performance that the SRD model ordinarily implies for Task 2. In producing such performance, the model relies on a preparatory mechanism similar to ones that some previous theorists (e.g., Gottsdanker, 1979, 1980) have proposed.

Mean Task 2 RT as a function of SOA. On the basis of the preceding analysis, a more general equation may be constructed for the mean Task 2 RT. This equation has a form similar to ones in other related domains where there are probabilistic mixtures of alternative information-processing sequences (e.g., see Meyer et al., 1984, 1985; Yantis, Meyer, & Smith, 1991). Assuming that the SRD model's parameters are random variables, we sum the products of the respective conditional path probabilities and conditional Task 2 RTs, which thereby takes into account that across trials, any particular numerical SOA may lead to various paths of processing for Task 2. This yields

$$E[RT_2(SOA)] = \sum \{p(\text{Path } i \mid SOA) \times E[RT_2(SOA \mid \text{Path } i)]\}, \tag{17}$$

where the expected value $E[RT_2(SOA)]$ is the overall mean Task 2 RT implied by the SRD model as a function of the SOA.

Unfortunately, when the model's parameters are random variables, exact numerical values of the mean Task 2 RTs are difficult to derive from Equation 17. This difficulty arises because the terms $p(\text{Path } i \mid SOA)$ and $RT_2(SOA \mid \text{Path } i)$ contain various sums of conditionalized random variables and non-linear operators (see Table 3). Evaluating them requires dealing with rather complicated convolutions of distributions that do not necessarily lend themselves to simple closed-form solutions. For present purposes, we have therefore obtained approximate numerical values of theoretical mean RTs through computer simulations of the SRD model.

Yet despite the complexities associated with the preceding equations, they may be helpful in some additional ways. Under certain circumstances, we use them as a basis for estimating values of the parameters in our simulations (*Appendix 4*). Also, from plotting the theoretical Task 2 RT as a function of SOA, it is possible to learn more about the shapes of PRP curves that the SRD model implies.

Theoretical PRP Curves

When RTs for the alternative paths of information processing in Task 2 are plotted graphically, we see that the SRD model may produce several distinct families of theoretical PRP curves (Task 2 RT vs. SOA) whose shapes depend on the model's parameters. By examining each family in detail, one can better understand why PRP curves of both simulated and empirical mean Task 2 RTs appear as they do. This also helps set the stage for our subsequent discussion of parameter estimation (*Appendix 4*) and goodness-of-fit assessment.

Prototype PRP Curve

The families of PRP curves produced by the SRD model are all based on a single underlying prototype PRP curve, which appears in Figure 14. To depict the form of this curve most clearly, we assume for the moment that the model's parameters are constants. Also, we assume that the parameter values allow each of the five possible paths of processing between the Task 2 stimuli and responses to be taken throughout some interval of positive SOAs. These assumptions constrain the prototype PRP curve to have five linear segments, corresponding respectively to contributions from the five Task 2 RT equations introduced previously (Table 3). In what follows next, we discuss each segment and how it depends on the SRD model's parameters. After this discussion, later sections consider what PRP curves may emerge when these parameters are random variables rather than constants.

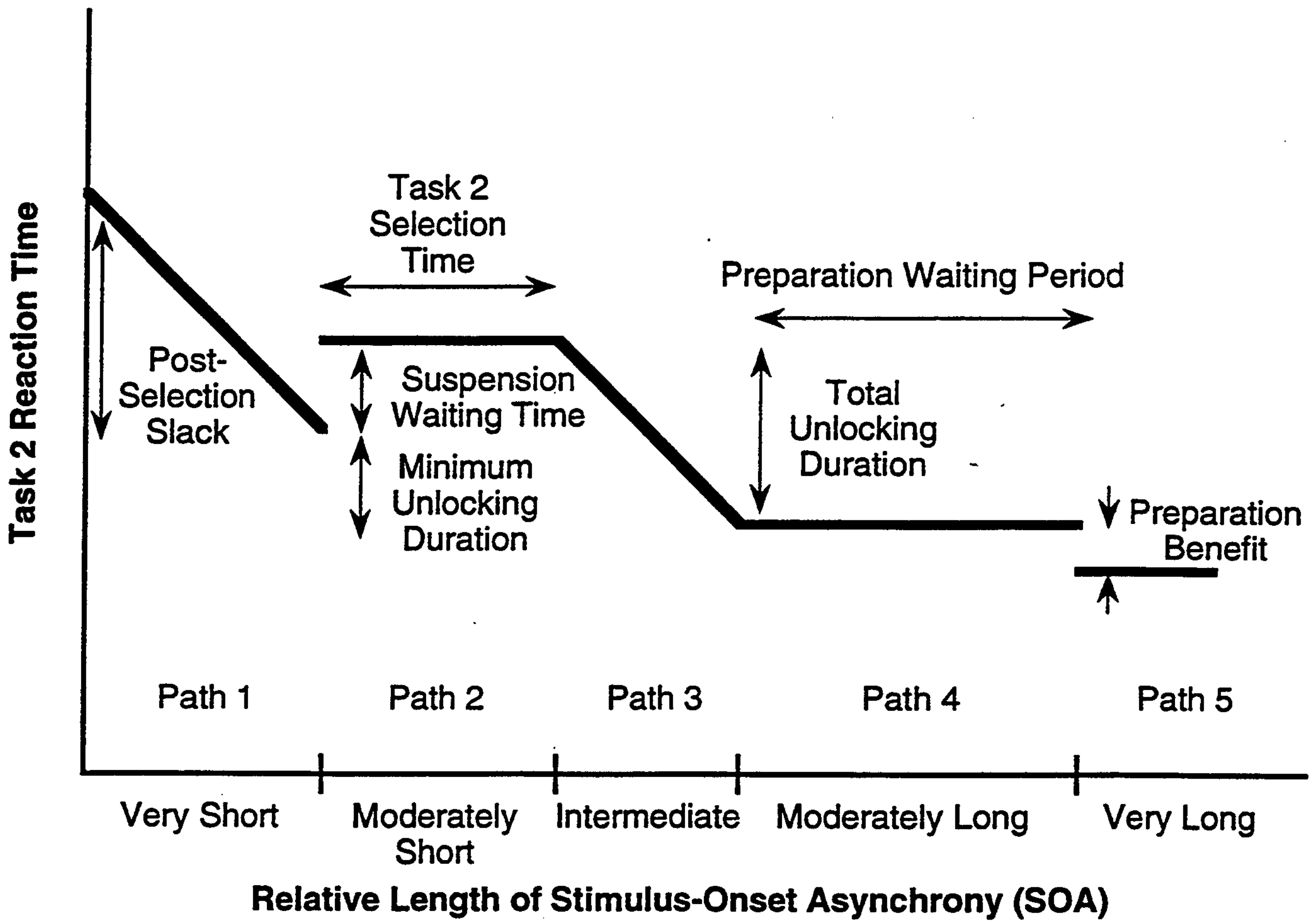

Figure 14. The prototype PRP curve implied by the SRD model when its parameters are constants that stay the same as the SOA increases from "very short" to "very long". Forming the curve are five linear segments that, from left to right, stem respectively from taking Paths 1 through 5 of processing for Task 2 (cf. Figures 10 through 13). Labels above the horizontal axis indicate which path is taken following each SOA, and labels on the prototype curve indicate which components of the theoretical Task 2 RT contribute to each of the curve's segments.

First segment. The RT equation for Path 1, which entails post-selection slack in Task 2, is the source of the prototype PRP curve's first (left-most diagonal) segment. This segment extends over an interval of very short SOAs. Here the Task 2 RT decreases linearly with a slope of -1 as the SOA increases and the post-selection slack correspondingly decreases, terminating in an intermediate valley (Figure 14). By construction (Inequality 2), the overall magnitude of this decrease equals the length of the post-selection slack at an SOA of zero (i.e., $t_{i1} + t_{s1} + t_u - t_{i2} - t_{s2}$). Thus, to the extent that stimulus identification and response selection for Task 1 are slow (i.e., $t_{i1} + t_{s1}$ is large) or stimulus identification and response selection for Task 2 are fast (i.e., $t_{i2} + t_{s2}$ is small), the initial Task 2 RT decrease will be large.

Second segment. Next, however, the prototype PRP curve jumps abruptly upward because of a contribution from the RT equation for Path 2, which entails mid-selection slack in Task 2. As mentioned before, the magnitude of this jump equals the suspension waiting time (t_w) that delays the resumption of Task 2 after the SRD model's executive process starts unlocking it. Insofar as t_w is large, it may even raise the Task 2 RTs back up to where they are when the SOA equals zero.[23] Furthermore, after jumping upward, the Task 2 RTs are constant over an interval of moderately short SOAs, yielding the second (upper horizontal) segment of the prototype PRP curve. This segment is flat and forms a plateau because the mid-selection slack (i.e., $t_v + t_w$) stays the same for all moderately short SOAs. The plateau's extent equals the difference between the left and right sides of Inequality 5, which is simply the Task 2 response-selection time, t_{s2}. So if Task 2 response selection is difficult, then the second segment will be relatively long.[24]

Third segment. At the right end of the second segment, Path 3 and the RT equation for it lead the prototype PRP curve to descend again toward baseline. Associated with this next drop is pre-selection slack that decreases steadily as the SOA increases, yielding a third (middle diagonal) segment over an interval of intermediate SOAs. Because the third segment's slope is -1, the total decrease of the Task 2 RT that results from it equals $t_v + t_w$ (i.e., the difference between the left and right sides of Inequality 8, which also equals the magnitude of the mid-selection slack).

Fourth segment. After the interval of intermediate SOAs, the prototype PRP curve reaches a "neutral" baseline, corresponding to its fourth (next-to-lowest) segment in Figure 14. Here the Task 2 RT has no temporal slack. The neutral baseline, which comes from the RT equation for Path 4, occurs over an interval of moderately long SOAs. The length of this interval is simply the difference between the left and right sides of Inequality 11, which is linearly related to the preparation waiting time of the SRD model's executive process. Thus, if t_y is large, then the prototype curve may remain at the neutral RT baseline for an extended period, until the SOA becomes very long.

Fifth segment. Over the interval of very long SOAs, the prototype PRP curve falls to its lowest level, whose source is Path 5. The contribution of the RT equation for Path 5 is embodied by the fifth (right-most) segment in Figure 14. Along this segment, the Task 2 RTs are minimal because the preparation-benefit time, t_{p2}, is subtracted from the total movement-production time.

Qualifications about the prototype curve. Of course, the prototype PRP curve will never be observed directly in an experiment. Across experimental trials, real subjects' performance -- like the SRD model's parameters -- may vary randomly, causing the prototype's individual segments to be smeared beyond recognition when viewed in terms of empirical mean Task 2 RTs. Nevertheless, some instructive insights are provided by examining the form of the prototype in the absence of such

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[23] This would happen if the suspension waiting time has the same magnitude as the post-selection slack at zero SOA (i.e., $t_w = t_{i1} + t_{s1} + t_u - t_{i2} - t_{s2}$).

[24] As Welford (1967) noted, PRP curves may have relatively shallow (near zero) slopes at intermediate SOAs because there is variability in the time taken to complete Task 1, which in turn affects when a single-channel mechanism becomes available for Task 2. Without such variability, single-channel mechanisms and response-selection bottleneck models (Pashler, 1984, 1990, 1993) -- in their simplest form -- imply that PRP curves consist of two linear RT segments, the first having a slope of -1 at relatively short SOAs, and the second having a slope of zero at longer SOAs (Welford, 1959, 1967). In contrast, the SRD model implies shallow slopes at "moderately short" SOAs even when the underlying processes are entirely deterministic.

randomness. As a result, the contributions of underlying component processes to Task 2 RTs become more clearly visible at each SOA.

PRP-Curve Families

On the basis of the prototype PRP curve (Figure 14), the SRD model can produce several distinct families of theoretical PRP curves whose shapes are more or less similar to the prototype. For now, our discussion considers four such families, which appear in Figure 15 (Panels A through C). They do not exhaust the entire range of possibilities, but they do constitute some especially instructive cases.

The PRP-curve families in Figure 15 have a number of salient properties. Within each family, the only parameter that changes from one curve to the next is the Task 2 response-selection time (t_{s2}), corresponding to systematic variations of response-selection difficulty; all the SRD model's other parameters are assumed to be constant for the different curves of a family. Consequently, all the depicted curves consist of concatenated linear segments. However, across families, other parameters besides the Task 2 response-selection time change systematically, causing the shapes of the curves in one family to differ from those in another. To be specific, *Family 1* contains PRP curves such that each involves some post-selection slack and has five segments like the prototype curve does (cf. Figure 14). *Family 2* contains PRP curves such that each involves a relatively long ocular-orientation time, which introduces pre-identification slack instead of post-selection slack in Task 2 RTs at very short SOAs.[25] This change again yields five segments per curve, but the left-most segments have somewhat different positions and extents than those of the curves in Family 1. *Family 3* contains PRP curves such that each involves relatively fast Task 1 processes, which introduce mid-selection instead of post-selection slack at very short SOAs, yielding four rather than five segments per curve. Lastly, *Family 4* contains PRP curves such that each involves a relatively short unlocking-onset latency, which introduces pre-selection instead of post-selection slack at very short SOAs, yielding only three segments per curve. Viewed overall, these families of curves represent a range of possibilities that may emerge from the SRD model, depending on the particular values of its parameters. In some cases (e.g., Family 4), quantitative relations among the PRP curves of a family are similar to what a simple response-selection bottleneck model might imply. Testing the SRD model and evaluating it versus other competitors therefore requires careful thought and control over the parameter values that an experiment entails.

In the next subsections, we discuss each of the above PRP-curve families more fully. After the shapes of their curves have been examined closely, we consider the average PRP curves that emerge from them when the SRD model's parameters are random variables rather than constants. Readers who want to skip the following detailed discourse may proceed directly to the next main section entitled *Protocol for Simulations with The SRD Model.*

Family 1: PRP curves with post-selection slack. The first relevant family of PRP curves stems from conditions under which, depending on the SOA, each of the five possible paths of processing from the Task 2 stimulus to the Task 2 response is taken. Consistent with prior discussion, these conditions introduce post-selection slack in the Task 2 RT at very short SOAs (Figure 10). As a result, Family 1 contains PRP curves whose shapes are all highly similar to the prototype curve. However, because post-selection slack is present here, and because the underlying Task 2 response-selection time changes from one curve to the next, the contributions of response-selection difficulty to the curves of Family 1 differ as a function of the SOA. This difference makes these curves "diverge" (i.e., become vertically farther apart) from each other as the SOA increases.

[25] By definition, *pre-identification slack* is a period of time during which identification of the stimulus for a task has not yet begun even though the stimulus has been presented. Task 2 would include such slack if a visual stimulus for it occurs at a peripheral location to which the eyes are moved only after the stimulus's onset.

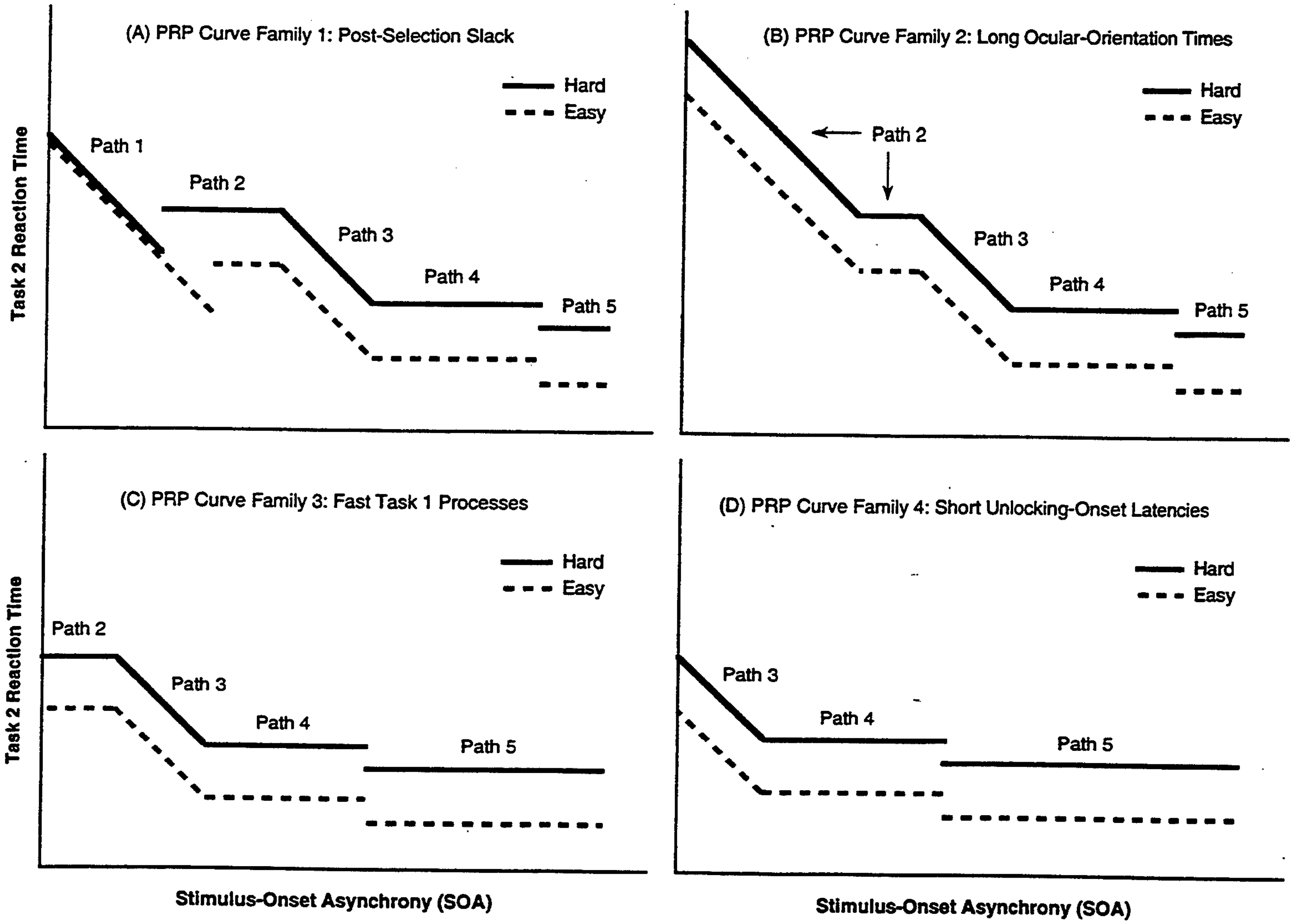

Figure 15. Four representative families of PRP curves that may be produced by the SRD model, depending on the relative magnitudes of its parameters. Labels next to the curves indicate which path of processing in Task 2 underlies each linear segment. Dashed and solid curves illustrate cases in which response selection for Task 2 is respectively easy and hard. Within each family, other parameters are assumed to be constant. Across families, some parameters change systematically. Panel A: Five-segment PRP curves of Family 1. Because these curves -- like the original prototype (cf. Figure 14) -- contain post-selection slack at very short SOAs, they embody an interaction between SOA and Task 2 response-selection difficulty. Panel B: Five-segment PRP curves of Family 2. Because these curves stem from long Task 2 ocular-orientation times, Path 1 of processing does not contribute to them at very short SOAs, and they contain no post-selection slack, so the effects of SOA and Task 2 response-selection difficulty are additive over the entire SOA range. Panel C: Four-segment PRP curves of Family 3. Because these curves stem from relatively fast Task 1 processes, they too do not involve Path 1 of processing or post-selection slack at very short SOAs, so the effects of SOA and Task 2 response-selection difficulty are again additive over the entire SOA range. Panel D: Three-segment PRP curves of Family 4. Because these curves stem from a short unlocking-onset latency, neither Path 1 nor Path 2 of processing contributes to them, and they contain no post-selection or mid-selection slack, so the effects of SOA are less but still additive with those of Task 2 response-selection difficulty.

For example, Panel A of Figure 15 shows two representative PRP curves of Family 1. Here the upper solid curve has five segments corresponding respectively to contributions from Paths 1 through 5 in Task 2. Similarly, the lower dashed curve has five segments . Nevertheless, an important difference exists between these curves. The lower curve involves a shorter Task 2 response-selection time (t^*_{s2}) than does the upper curve (t_{s2}). Consequently, the lower curve's segments at intermediate and long SOAs fall a constant amount (i.e., $t_{s2} - t^*_{s2}$) below those of the upper curve. This is because the response-selection times contribute additively to the Task 2 RTs for these SOAs (Table 3). In contrast, at very short SOAs, the lower and upper PRP curves of Family 1 are superimposed. This is because the post-selection slack along Path 1 absorbs the Task 2 response-selection times, so differences between them do not affect the Task 2 RT when the SOA is very short. Thus, for Family 1, the SOA and response-selection difficulty have interactive effects, which cause the PRP curves to diverge as the SOA increases. As our subsequent computer simulations demonstrate, some previous empirical studies with the PRP procedure (e.g., Hawkins, Rodriguez, & Reicher, 1979; Karlin & Kestenbaum, 1968) have satisfied the preconditions that enable such divergence to occur.

Yet PRP curves need not always manifest interactions between the effects of SOA and Task 2 response-selection difficulty. On the contrary, the SRD model implies that there are at least three other families of curves for which SOA and Task 2 response-selection difficulty have strictly additive effects over the entire positive range of SOAs. This additivity stems from conditions under which, for various reasons, Path 1 of processing is never taken during Task 2, so no post-selection slack contributes to Task 2 RTs at very short SOAs.

Family 2: PRP curves with long ocular-orientation times. For example, a long ocular-orientation time can preclude post-selection slack, instead creating pre-identification slack in Task 2 RTs at very short SOAs (see Footnote 24). This yields a second family of theoretical PRP curves whose paired members are strictly "parallel" (i.e., the same vertical distance apart at all positive SOAs), embodying additive effects of SOA and Task 2 response-selection difficulty. Family 2 is produced by the SRD model when its parameters have the same values as those used to form Family 1, except that we replace a short (e.g., zero) ocular-orientation time (t_{o2}) with a markedly longer one (t^*_{o2}), as would be required if Tasks 1 and 2 involve spatially separate visual stimuli. In particular, suppose that $t^*_{o2} > t_{i1} + t_{s1} + t_u - t_{i2} - t^*_{s2} > 0$, and $t^*_{o2} < t_{i1} + t_{s1} + t_u - t_{i2}$, where t_{i1} and t_{i2} are stimulus-identification times for Tasks 1 and 2, respectively, t_{s1} and t^*_{s2} are response-selection times for Task 1 and the easy Task 2, and t_u is the unlocking-onset latency of the SRD model's executive process. Then as Panel B of Figure 15 shows, Family 2 includes parallel PRP curves that have five segments per curve, but that are different from those of Family 1 in some salient respects.

Specifically, the left-most diagonal segments of Family 2's curves stem from the pre-identification slack created through the long ocular-orientation time during Task 2. Given this slack, the heights of these segments are governed by the RT equation for Path 2 rather than the RT equation for Path 1. As a result, the curves of Family 2 are more elevated and separated than those of Family 1 at very short SOAs. This is because the RT equation for Path 2 contains both the Task 2 ocular-orientation and response-selection times, whereas the RT equation for Path 1 contains neither (Table 3). Also, as the SOA increases from zero, the effects of the long ocular-orientation time and concomitant pre-identification slack diminish in Family 2, leading its PRP curves to decline steadily at first. Using the term max(0, t^*_{o2} - SOA) from the RT equation for Path 2, we may calculate how large this initial decline is; it simply equals t^*_{o2} , the long ocular-orientation time.

Following the initial decline of the curves in Family 2, their other segments at longer SOAs are similar to those of the curves in Family 1. Such similarity occurs because once the SOA exceeds the ocular-orientation time, Paths 2 through 5 are again taken during Task 2 as the SOA increases further, leading to successive periods of mid-selection slack, pre-selection slack, and so forth (Figures 11 through 13). It can therefore be shown that the second family's PRP curves embody additive effects of SOA and Task 2 response-selection difficulty over the entire range of positive

SOAs.[26] In effect, the long ocular-orientation time eliminates the SOA-by-difficulty interaction that characterized the curves of Family 1. As our subsequent computer simulations demonstrate, conditions like this may have produced additive effects of SOA and response-selection difficulty in some past empirical studies with the PRP procedure (e.g., Hawkins et al., 1979; McCann & Johnston, 1992, Exp. 2).

Family 3: PRP curves based on relatively fast Task 1 processes. There is a third family whose PRP curves embody strictly additive effects of SOA and Task 2 response-selection difficulty. Family 3 stems from conditions like those that yield Family 1, except that the Task 1 stimulus-identification and/or response-selection times are markedly shorter than before. For example, suppose we replace the prior Task 1 stimulus-identification time t_{i1} with a smaller value, t^*_{i1} , such that $t^*_{i1} = t_{i2} + t^*_{s2} - t_{s1} - t_u$. Then this precludes Path 1 from being taken during Task 2, thereby eliminating post-selection slack in Task 2 RTs at very short SOAs (Table 3). Instead, the Task 2 RTs are based on Path 2 when the SOA is very short. As a result, the PRP curves of Family 3 look like those in Panel C of Figure 15.

Several interesting properties of Family 3's curves should be noted. Each of them has four rather than five segments, corresponding respectively to contributions by Paths 2 through 5 of processing for Task 2. The curves' left-most segments are horizontal; they stem from the RT equation for Path 2 (Figure 11), which contains mid-selection slack whose duration is independent of the SOA (assuming $t_{o2} \leq 0$). Also, as in Family 2, the PRP curves of Family 3 are separated vertically from each other by an amount that always equals the difference in their respective response-selection times (i.e., $t_{s2} - t^*_{s2}$). Thus, the effects of response-selection difficulty and SOA are additive for Family 3. As our later computer simulations demonstrate, such additivity may have occurred because of relatively fast Task 1 processes in some past studies with the PRP procedure (e.g., Hawkins et al., 1979; Pashler & Johnston, 1989).

Family 4: PRP curves based on relatively short unlocking-onset latencies. Finally, there is a fourth even simpler family of PRP curves that the SRD model can produce. They stem from conditions under which not only Task 1 stimulus identification is fast, but also the unlocking-onset latency of the executive process is relatively short. In particular, suppose that the model's parameters have the same values as for Family 3, except that the unlocking-onset latency t_u is replaced with a smaller value t^*_u such that $t_u - t^*_u = t^*_{s2}$. Then even at short SOAs, neither Path 1 nor Path 2 of processing would be taken for Task 2, so the Task 2 RTs would contain neither post-selection nor mid-selection slack. Instead, the Task 2 RTs would contain pre-selection slack when the SOA is short. This yields PRP curves that come from Family 4, as depicted in Panel D of Figure 15.

The shapes of these curves embody an additional constraint imposed by the short unlocking-onset latency. Given this constraint, the Task 2 RTs are based on only Paths 3, 4, and 5 as the SOA increases from zero, so Family 4 has only three segments per PRP curve. Because the RT equations for Paths 3, 4, and 5 all include additive combinations of SOA and Task 2 response-selection time (Table 3), response-selection difficulty and SOA have strictly additive effects on the curves of Family 4. Family 4 therefore contains "parallel" PRP curves with shapes similar to those implied by a response-selection bottleneck model.

Substantive implications. The preceding discussion demonstrates that the SRD model may produce multiple families of theoretical PRP curves, whose shapes and quantitative relations to each other depend on the magnitudes of the model's parameters. Within one family, the curves exhibit

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[26] For example, let $t^*_{o2} = t_{i1} + t_{s1} + t_u - t_{i2} - t^*_{s2} + x$, where $0 < x \leq t^*_{s2}$. Next substitute the right side of this equation into the right side of the RT equation for Path 2 and subtract the right side of the RT equation for Path 1 from it. This yields the amount by which the left-most diagonal segment of the upper PRP curve in Panel B of Figure 15 is elevated relative to the left-most diagonal segments in Panel A of Figure 15. The elevation is simply $x + t_w + t_{s2} - t^*_{s2}$, which includes the ocular-orientation time, suspension waiting time, and times for difficult versus easy response selection. Similarly, the left-most diagonal segment of the lower PRP curve in Panel B of Figure 15 is elevated by an amount that equals $x + t_w$ relative to the corresponding left-most segments of the PRP curves in Panel A of Figure 15. Thus, the left-most diagonal segments of the two PRP curves in Panel B of Figure 15 are separated vertically by the difference in the response-selection times, $t_{s2} - t^*_{s2}$, which also equals the vertical separation between these curves at longer SOAs.

salient interactions between effects of SOA and Task 2 response-selection difficulty (Figure 15, Panel A), whereas other families contain curves that exhibit additive effects (e.g., Figure 15, Panels B, C, and D). SOA-by-difficulty interactions occur only under certain conditions: the ocular-orientation time must be short, the unlocking-onset latency must be long, and Task 1 processes (i.e., stimulus identification and response selection) must be relatively slow. If any of these requirements is not met, then SOA and response-selection difficulty can affect Task 2 RTs additively, even though the SRD model has the capacity to select responses concurrently for multiple tasks. Also, according to the model, the complexity of PRP curves can differ systematically; there can be anywhere from three to five underlying segments per curve, depending on which paths of processing are taken during Task 2 as the SOA increases. In light of these considerations, empirical PRP curves must be evaluated carefully to determine exactly what conclusions they support.

Theoretical PRP Curve for Mean Task 2 RTs

It must be recognized again, however, that the preceding discourse is not entirely general. We began by assuming that the parameters of the SRD model are constants. If the parameters are instead treated as random variables, which would be more realistic, then the model does not typically produce mean Task 2 RTs for which the PRP curves are linearly segmented and all come from the same family. Rather, the theoretical PRP curves of mean Task 2 RTs will be "smeared" versions of the deterministic ones shown in Figure 15; they will have smooth shapes that involve mixtures of curves from various families. For reasons mentioned already, what these smooth shapes look like cannot be determined easily through the mixture equation of mean Task 2 RTs that was introduced earlier (Equation 17). Thus, we subsequently examine the shapes of theoretical PRP curves for mean Task 2 RTs obtained from computer simulations with the SRD model.

For example, Figure 16 illustrates one "smooth" PRP curve of mean Task 2 RTs that emerged from such a simulation. Here the model's parameters were random variables, and they led to various paths of processing for Task 2 at each SOA. As a result, the PRP curve in Figure 16 does not have five salient linear segments, even though the original deterministic prototype curve (Figure 14) did. Instead, the prototype's segments are now almost totally hidden, except for slight visual hints of a middle "shoulder" in the neighborhood of moderately short and intermediate SOAs, corresponding to the upper plateau of the prototype (i.e., Path 2 with mid-selection slack). The next section discusses more fully how our simulations were conducted to reach this and other important conclusions.

Protocol for Simulations with The SRD Model

To further demonstrate the applicability of the SRD model and its EPIC information-processing architecture, we have used them in computer simulations of representative past studies with the PRP procedure. This lets us make detailed quantitative comparisons between outputs produced by the model and empirical RT data obtained across various experimental contexts. Although good fits between the model's outputs and data do not definitively prove that the model is correct, they at least establish it as a serious theoretical contender.

Before our simulations began, software modules were programmed for each component of the EPIC architecture, including its perceptual processors, motor processors, cognitive processor, and memory stores. These modules have been written in the Common LISP programming language and embody EPIC's basic assumptions (Table 1 and Figure 7) in executable form. The functional properties of the architecture have remained the same throughout our simulations, just as real subjects' underlying perceptual-motor and cognitive mechanisms presumably do during typical laboratory testing.

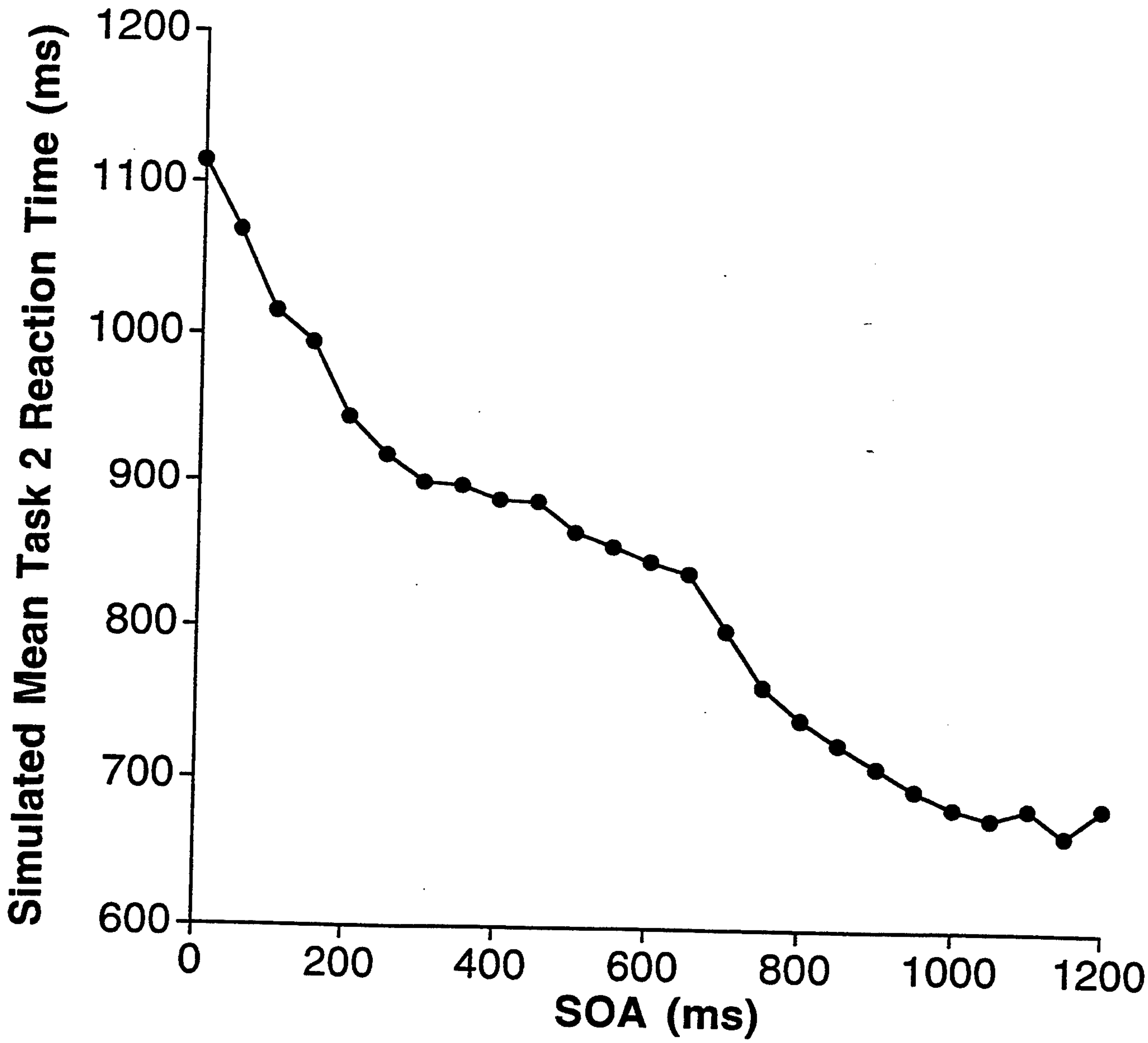

Figure 16. A PRP curve of simulated mean Task 2 RTs produced by the SRD model when its parameters vary randomly across a series of trials. Underlying this curve is a mixture of contributions from various families of theoretical PRP curves (Figure 15), and so the simulated curve's shape looks like a smeared version of the original prototype PRP curve (cf. Figure 14).

Steps in Each Simulation

Each simulation presented here involved several steps. Together, these steps are analogous to ones that an experimenter would take in trying to replicate an actual empirical study with human subjects.

Selection of empirical PRP study. For each simulation, we first chose an important past empirical PRP study. It typically included several experimental conditions across which the stimulus modalities, response modalities, number of alternative S-R pairs, levels of S-R compatibility, and/or other independent variables differ systematically. Observed and simulated effects of these variables are directly relevant to the SRD model versus other alternatives such as the single-channel hypothesis, bottleneck models, and unitary-resource theory.

Preparation of environment-simulation program. To help mimic the chosen study, we prepared an *environment-simulation program* whose inputs and outputs recreated the study's task environment. This program presented stimulus inputs to EPIC's sensory components at appropriate times, and it transduced response outputs from EPIC's effector components.

Preparation of executive and task production rules. In addition, we prepared three sets of production rules according to the SRD model (e.g., see *Appendices 1* through *3*). Two of these rule sets respectively performed Task 1 and Task 2 of the chosen study. The third rule set implemented the model's executive process.

Together, the executive and task rule sets -- along with the modules of the EPIC architecture -- constituted a *subject-simulation program*. The operations of this program putatively mimicked subjects' mental and physical activities under the various conditions of the chosen study. Across conditions, the task rule sets changed to characterize the effects of stimulus modality, response modality, S-R numerosity, and S-R compatibility, but the executive rule set always used the same task-scheduling strategy (Figures 8 and 9) except in a few special cases discussed elsewhere (Meyer & Kieras, 1997b).

Assignment of numerical parameter values. After preparing the production-rule sets for the chosen study, we assigned numerical values to parameters of the SRD model and EPIC architecture. Some parameters were *context independent*; they had the same numerical values across all simulations. Other parameters were *context dependent*; their values changed systematically, depending on the chosen study's design (e.g., modalities of stimuli and responses). However, for the context-dependent parameters, we have made concerted efforts to use the same values across the different conditions of each study. For example, in simulating results from sets of conditions that crossed stimulus modality (visual vs. auditory) with response modality (manual vs. vocal), our stimulus-identification times had the same values regardless of the response modality, and our response-transduction times had the same values regardless of the stimulus modality. Such constraints limited the SRD model to have relatively few degrees of freedom for achieving good fits between simulated and empirical RTs.

The parameters used here also had another important characteristic. Some of them were treated as random variables; their numerical values varied stochastically from trial to trial under each condition. For these parameters, we assigned the means of their distributions on an a priori basis before each simulation started. Further details about this assignment are presented below.

Execution of simulation programs. For each condition of the chosen study, we executed the environment-simulation and subject-simulation programs in combination, letting them interact with each other throughout a series of simulated test trials. During every trial, Task 1 and Task 2 stimuli -- separated by some SOA -- were presented to EPIC's perceptual processors. The stimuli were sampled in accord with the study's experimental design. Given each stimulus, EPIC's cognitive processor performed input-output transformations, using the prespecified task and executive production rules of the SRD model. Responses selected by the cognitive processor were sent to EPIC's motor processors, which converted them to overt movements. The environment-simulation program transduced each response movement, recording its latency and identity for later analysis. The durations of these intervening operations depended on the values that we assigned to the architecture's and model's parameters.

Across simulated test trials, EPIC's cognitive-processor cycle duration and other associated parameters varied randomly.[27] This yielded Monte Carlo distributions of RTs that constitute the SRD model's account of subjects' performance for the chosen study. We conducted enough trials that the means of these distributions could be estimated with reasonably high precision (standard errors on the order of 10 ms or less). Consequently, on the order of 1000 to 2000 simulation trials were typically run per condition.

Data analysis. We analyzed the RTs from each simulation, comparing them quantitatively to the data reported in the chosen study. This involved evaluating the goodness-of-fit between simulated and empirical PRP curves, as discussed more fully later. These evaluations let us assess how well the SRD model accounts for the data.

No attempt is made here to model variations of response accuracy. Instead, our simulations have been constrained for now to produce error-free responses. We want initially to obtain precise accounts of RT data when response accuracy is high, as in most past empirical studies with the PRP procedure. In principle, however, the SRD model can be extended to account for patterns of erroneous responses and speed-accuracy tradeoffs, which are important for a comprehensive understanding of human information processing (Luce, 1986; Meyer et al., 1988b, 1988c; Pachella, 1974).[28]

Further Details about Assigned Parameter Values

Further details about the assignment of numerical values to parameters of EPIC and the SRD model appear in Table 2, which was introduced earlier. There we have indicated which parameters are context dependent or independent, and whether they serve as constants or random (stochastic) variables within each of our simulation runs. Also listed are numerical values that the pre-assigned means of the context-independent parameters have.

Context-independent parameters. The means (i.e., statistical expected values) of the context-independent stochastic parameters, which stayed the same across all simulations, have been set on the basis of informal "guesstimation." In such cases, we have assigned their numerical values through intuition and examination of past literature from experimental psychology and human-factors engineering (e.g., Atkinson et al., 1988; Boff et al., 1986; Woodworth & Schlosberg, 1954). Guesstimation is needed because appropriate values of some parameters cannot be formally estimated or iteratively approximated from the empirical results of the PRP studies on which our simulations focus (i.e., the guesstimated parameters are not explicitly "identifiable"; they have effects only in conjunction with those of other parameters).

Although the values of the context-independent parameters are guesstimated, including them here has some important benefits. Their consistency across simulations limits the degrees of freedom that the SRD model has for fitting empirical data, thereby increasing the model's parsimony. Also, the context-independent parameters provide constraints that help us formally estimate appropriate numerical values of the context-dependent parameters (*Appendix 4*).

For example, the cycle duration (t_c) of EPIC's cognitive processor is among the present context-independent parameters (Table 2); it always had a mean of 50 ms. Correspondingly, the *working-memory gating time* (t_g) of the cognitive processor had a mean of 25 ms. These assignments are consistent with results of empirical studies that putatively manifest the cyclicity of human information processing (e.g., Callaway & Yeager, 1960; Dehaene, 1992, 1993; Kristofferson, 1967).

[27] On each simulated test trial, values for the stochastic parameters were sampled from uniform distributions whose coefficients of variation (i.e., ratios of standard deviation to mean) equaled 0.2, consistent with typical relations between empirical RT means and standard deviations.

[28] To account for incorrect responses and speed-accuracy trade-offs during multiple-task performance, EPIC and the SRD model can be augmented with a variety of additional mechanisms (Kieras & Meyer, 1996). For example, through extensions of the model's rule sets and EPIC's information-processing modules, errors might occur on the basis of fast guesses, processing deadlines, faulty comparisons between production-rule conditions and working-memory contents, and loss of information from working memory.

By using the same mean values of the cycle duration and working-memory gating time throughout our simulations, it becomes possible to estimate the values of other parameters (e.g., the mean number of response-selection cycles, n_s) under particular conditions.

Some parameters of EPIC's motor processors are also context independent. For present purposes, we have assumed that the number of movement features (n_f) prepared to produce an overt response is typically two (e.g., the hand and finger of a manual keypress).[29] Furthermore, the time per movement feature (t_f) taken by each motor processor in producing a response has an assumed mean of 50 ms, as do the motor processors' action initiation times (t_a). These assignments adhere to results of some previous research on human motor programming (e.g., Abrams & Jonides, 1989; Gordon & Meyer, 1984; Meyer & Gordon, 1985; Miller, 1982; Rosenbaum, 1980; Rosenbaum & Kornblum, 1982; Yaniv et al., 1990). Given this adherence, additional perceptual and motor processor parameters then become formally estimable.

Context-dependent parameters. The means of our context-dependent stochastic parameters, which change systematically across simulation runs, have been set not only through informal guesstimation but also through formal estimation and iterative search algorithms. To estimate appropriate values of these parameters, we rely on the theoretical RT equations introduced earlier, applying them to subsets of data from the empirical studies on which our simulations focus (*Appendix 4*). However, because these equations cannot always be easily solved to obtain the desired values, we have also relied on iterative searches during simulation runs to identify approximate values of parameters that maximize the SRD model's goodness-of-fit. As discussed more fully later, our estimation techniques let us precisely specify how many degrees-of-freedom the model has for producing good fits, from which we can then evaluate the model's overall success versus other competing theoretical alternatives.

For example, among the estimable context-dependent parameters are several perceptual-motor ones (Table 2). They include the times that EPIC's perceptual processors takes to detect and identify stimulus inputs (t_d and t_i). The response transduction times (t_r) of our environment-simulation program are also context-dependent parameters, as are some of the component times contributed by the task and executive processes of the SRD model. The means of these parameters may change systematically across conditions, because we expect them to help account for effects of factors such as stimulus intensity and discriminability, S-R compatibility and numerosity, and response modality.

Comparative Simulations with The SRD Model

Using our general simulation protocol, the first simulations to be reported here provide instructive comparisons between alternative theoretical accounts of results from empirical PRP studies. On the basis of these comparisons, we show that the SRD model fits some available data much better than does a simple response-selection bottleneck model. Also, we show that there is strong justification for including certain key elements (e.g., deferred-to-immediate mode shift, suspension waiting time, and anticipatory movement-feature preparation) as part of the SRD model's executive process.

It should be stressed that the SRD model did not emerge spontaneously in its present mature form. Rather, during the model's initial development, we tested several preliminary versions of it. Such tests reveal that each executive-process component may contribute significantly to an overall account of empirical RT data. In what comes next, we describe one representative empirical study with the PRP procedure that helped us reach these insights. After a summary of the methodology and results from this study, simulations with the response-selection bottleneck model and preliminary versions of the SRD model are reported to examine how well they each perform.

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29 Under other circumstances, the number of requisite movement features might be more than two. For example, to characterize movements made in a dual-task situation with continous manual tracking and discrete choice reactions, we (Kieras & Meyer, 1995, 1996) have assumed that five features are involved, including the hand (right or left), the movement style (joystick plying or key pressing), the movement direction (for joystick plying), the movement extent (for joystick plying), and the finger (for key pressing).

A Representative PRP Study

Our initial simulations focus on a PRP study by Hawkins et al. (1979). The procedure and results of this study are noteworthy in several respects. Hawkins et al. (1979) had subjects perform various types of Task 1, across which the stimuli were either auditory or visual, and the responses were either vocal or manual. Also included were a manipulation of Task 2 response-selection difficulty and a broad range of SOAs with numerous intermediate values. This design yields detailed PRP curves with systematic additivities and interactions among several factor effects, which offer a challenging context in which to evaluate the SRD model.

Specifically, there is one key set of conditions in Hawkins et al.'s (1979) study that concern us first. Here, Task 1 required manual choice reactions (left-hand finger presses) to auditory stimuli (tones), and Task 2 required manual choice reactions (right-hand finger presses) to visual stimuli (digits). The difficulty of the response-selection process for Task 2 was varied by having subjects deal with either two or eight alternative S-R pairs during Task 2.[30] RTs in Tasks 1 and 2 were measured as a function of the SOA and Task 2 difficulty.

Results from Hawkins et al. Some results from these measurements appear in Figure 17. Here the mean RTs in Task 1 (unfilled circles and triangles) are moderate (about 630 ms on average) and vary little across the SOAs (approximate standard error of each mean RT = 10 ms). These results replicate ones obtained by other investigators (e.g., Karlin & Kestenbaum, 1968; McCann & Johnston, 1992; Pashler, 1984, 1990; Pashler & Johnston, 1989). They are consistent with typical instructions for the PRP procedure, which emphasize completing Task 1 quickly regardless of the SOA and Task 2 response-selection difficulty. Likewise replicating results from previous PRP studies, Hawkins et al. (1979) found substantial PRP effects during Task 2 (Figure 17, filled circles and triangles). The mean Task 2 RTs are over 400 ms greater at the shortest (0 ms) SOA than at the longest (1200 ms) SOA.

In addition, there is an interesting pattern of response-selection difficulty effects on these mean Task 2 RTs. At intermediate and long (greater than 200 ms) SOAs, the Task 2 responses are much slower on average in the condition with eight S-R pairs than in the condition with two S-R pairs (Figure 17, filled circles vs. filled triangles; mean difficulty effect about 200 ms at the longest SOA). This temporally-localized difficulty effect is reliable compared to standard errors of the mean Task 2 RTs, which equal about 10 ms on average. At the shorter (less than 200 ms) SOAs, however, the number of S-R pairs affects the Task 2 RTs much less (only about 35 ms). Thus, overall, a substantial interaction is present between the effects of SOA and response-selection difficulty on mean Task 2 RTs in Hawkins et al.'s (1979) PRP study with an auditory-manual Task 1. This interaction replicates and extends results reported by Karlin and Kestenbaum (1968; see Figure 3). It is also consistent with the first family of theoretical PRP curves that the SRD model can produce (Figure 15, Panel A).

Theoretical implications. Given the benchmark results reported by Hawkins et al. (1979), tests may be conducted to assess how well various models account for subjects' performance under the PRP procedure. Pursuing this possibility, we next present a computer simulation that applies a simple response-selection bottleneck model in an attempt to fit the mean RTs in Figure 17. Then a simulation with the SRD model will be presented, showing that it actually fits Hawkins et al.'s results much better than does the bottleneck model.

[30] When Task 2 involved two S-R pairs, the stimuli were the digits 2 and 3, and the responses were key presses with the right-hand index and middle fingers, respectively. When Task 2 involved eight S-R pairs, the stimuli were the digits 2 through 9; for four of them (2, 5, 6, and 9), subjects pressed the right-hand index finger key, and for the other four (3, 4, 7, and 8), they pressed the right-hand middle finger key.

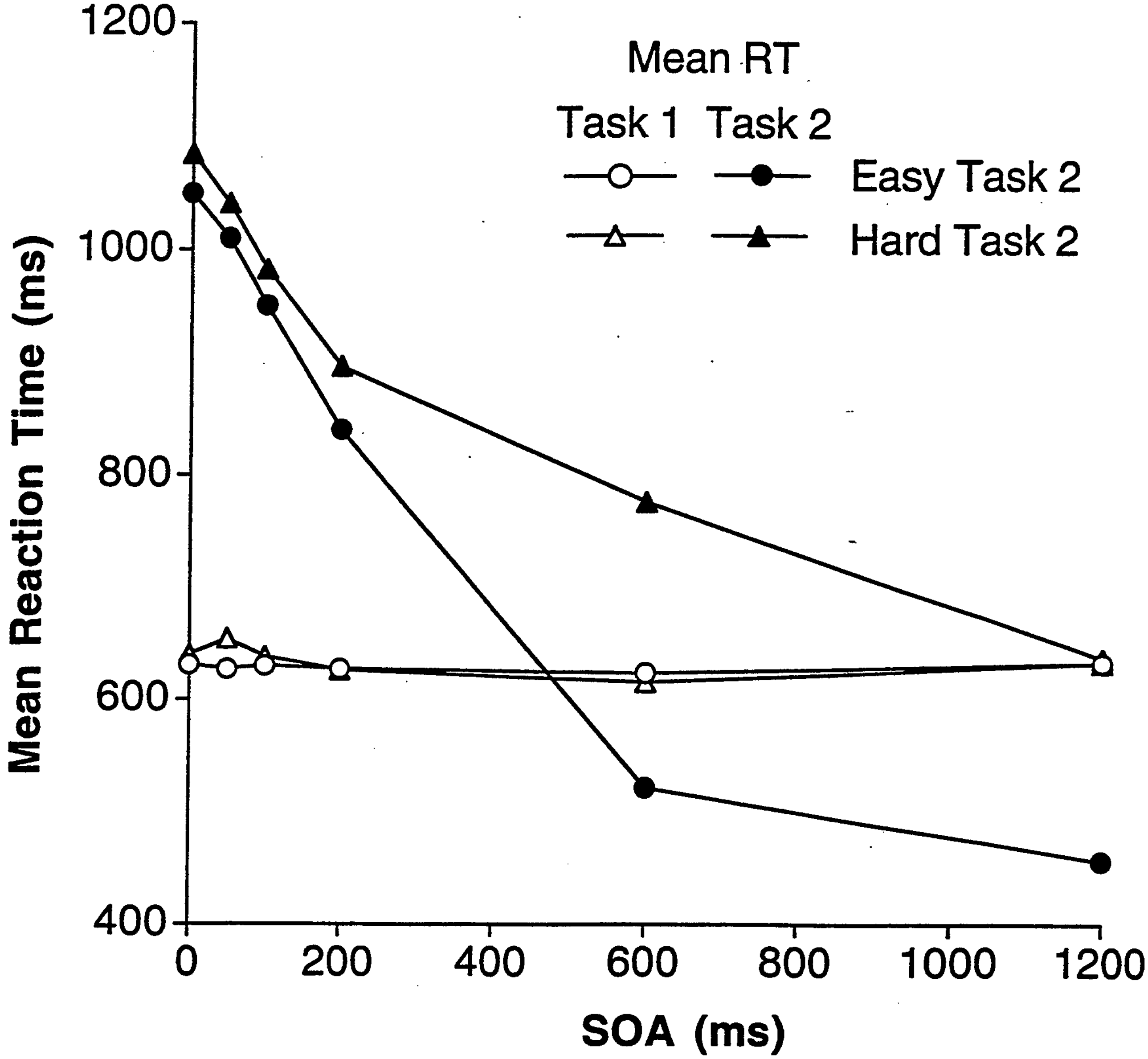

Figure 17. Results from Hawkins et al.'s (1979) study with the PRP procedure. Filled circles and triangles represent mean Task 2 RTs obtained when response selection in Task 2 was respectively "easy" or "hard." The easy (circles) condition of Task 2 involved two visual-manual S-R pairs; the hard (triangles) condition involved eight visual-manual S-R pairs. Unfilled circles and triangles represent corresponding mean Task 1 RTs, which always involved two auditory-manual S-R pairs. Each mean RT has a standard error of approximately 10 ms. For Task 2, the interaction between effects of SOA and response-selection difficulty on mean RTs is reliable ($p < .01$). There are no such effects on mean Task 1 RTs.

Simulation with Response-Selection Bottleneck Model

To conduct simulations with the response-selection bottleneck model, we followed the general protocol outlined previously. This entailed three steps: (a) specifying a set of production rules that can be used to perform Hawkins et al.'s auditory-manual Task 1; (b) specifying two additional rule sets that can be used respectively to perform Hawkins et al.'s easy and difficult visual-manual Task 2; (c) specifying a set of executive production rules that emulate a response-selection bottleneck while coordinating task performance as required by the PRP procedure's standard instructions.

The executive production rules that we specified to emulate the response-selection bottleneck model are straight-forward. On each simulation trial, they withhold the note "GOAL DO TASK 2" from working memory until the Task 1 response has been selected and its movement production is well underway. This complete lockout scheduling precludes any temporal overlap between the response-selection processes for Tasks 1 and 2, just as the response-selection bottleneck model requires.

Using the executive and task production rules for the bottleneck model, we conducted a series of simulation trials under conditions like those in the PRP study by Hawkins et al. (1979). Our simulation relied on the EPIC architecture. Subject to constraints imposed by the bottleneck model's complete lockout scheduling, EPIC's context-dependent parameters were assigned numerical values that maximized the goodness-of-fit between simulated mean RTs and Hawkins et al.'s data.

Simulated mean RTs for auditory-manual Task 1. Some results from this simulation appear in the top panel of Figure 18. Here we have plotted empirical mean RTs (large circles and triangles on solid curves) versus simulated mean RTs (small circles and triangles on dashed curves) produced by the response-selection bottleneck model for Hawkins et al.'s (1979) auditory-manual Task 1. The obtained fit is very good; its root mean squared error (RMSE) does not exceed the standard errors of the empirical mean Task 1 RTs (6 vs. 10 ms, respectively).

Simulated mean RTs for visual-manual Task 2. In contrast, the bottleneck model produces a markedly poorer fit ($R^2 = .89$) between simulated and empirical mean Task 2 RTs for Hawkins et al.'s (1979) study. The bottom panel of Figure 18 illustrates how bad this fit is. Here the model's RMSE is quite large compared to the standard errors of the empirical mean Task 2 RTs (73 vs. 10 ms). Like the empirical mean Task 2 RTs (large symbols on solid curves), the simulated mean Task 2 RTs (small symbols on dashed curves) exhibit both large PRP effects at short SOAs and a large Task 2 response-selection difficulty effect at long SOAs. However, there is also a large difficulty effect on the simulated mean Task 2 RTs at the shortest SOA, unlike what occurred in the empirical mean Task 2 RTs. In essence, the response-selection bottleneck model fails to mimic the substantial interaction that Hawkins et al. (1979) found between SOA and difficulty effects on Task 2 RTs when Task 1 involves auditory-manual reactions.

Theoretical implications. The inability of the bottleneck model to account well for the empirical mean Task 2 RTs stems from its complete lockout scheduling of response selection. Because of such scheduling, response selection for Task 2 never starts until after Task 1 is essentially done, so the difficulty of Task 2 response selection propagates forward to affect Task 2 RTs regardless of the SOA (Figure 4). That this propagation did not occur in Hawkins et al.'s (1979) study when Task 1 involved auditory-manual choice reactions raises the need for a more veridical model whose scheduling algorithms have greater efficiency and flexibility. In particular, the SRD model, whose optimized executive process enables temporally overlapping response selection for Tasks 1 and 2 of the PRP procedure, may fulfill the latter need.

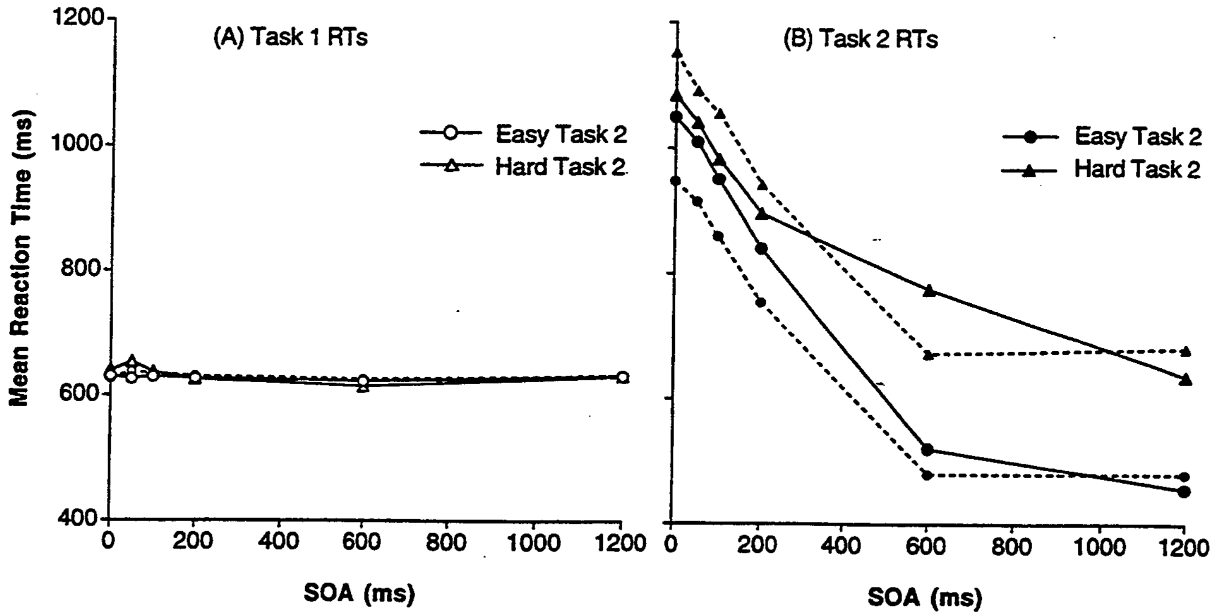

Figure 18. Results from simulations with the simple response-selection bottleneck model for Hawkins et al.'s (1979) PRP study involving an auditory-manual Task 1 and visual-manual Task 2. Large symbols on solid curves denote empirical mean RTs; small symbols on dashed curves denote simulated mean RTs. Circles and triangles represent RTs when Task 2 response selection was respectively easy or hard. Panel A: Goodness-of-fit between simulated and empirical mean Task 1 RTs. Panel B: Goodness-of-fit between simulated and empirical mean Task 2 RTs.

Simulation with Preliminary SRD Model

To confirm the preceding assessment, we next formulated a preliminary version of the SRD model. Its Task 1 and Task 2 production rules, which perform response selection for the two tasks, were the same as those in our previous simulation with the response-selection bottleneck model. All that changed from one model to the next was the executive process and its task-scheduling strategy.

As anticipated already (Figures 8 and 9), the preliminary SRD model's executive process put the notes "GOAL DO TASK 2" and "STRATEGY TASK 2 MODE IS DEFERRED" in working memory at the start of each simulated test trial, enabling Task 2 response selection to proceed concurrently with Task 1 response selection. In this respect, the preliminary SRD model was more efficient than the response-selection bottleneck model. However, we initially omitted some of the SRD model's other useful executive-optimization features.

For example, in its preliminary version, the executive process never shifted the Task 2 production rules from deferred to immediate response-transmission mode. Instead, regardless of progress made on Task 1, the Task 2 rules always operated in deferred mode, putting selected Task 2 responses temporarily in working memory. To accommodate the latter constraint while ultimately completing Task 2, the executive process permitted Task 2 responses to be sent from working memory to their motor processor after Task 1 was "done". This indirect route continued to be taken even at long SOAs, where Task 2 response selection does not start before Task 1 is done. The preliminary SRD model did not include any extra suspension waiting time or anticipatory movement preparation, which might contribute beneficially, were the response transmission mode to be shifted from deferred to immediate mode.

With the preliminary SRD model, we conducted further computer simulations under conditions like those described in the PRP study by Hawkins et al. (1979). Here, as before, EPIC's context-dependent parameters (e.g., stimulus-identification times) were assigned numerical values that maximized the goodness-of-fit between simulated and empirical mean RTs. This lets us directly compare the preliminary SRD model's goodness-of-fit versus what the response-selection bottleneck model previously achieved.

Simulated mean RTs for auditory-manual Task 1. Mean Task 1 RTs produced by the preliminary SRD model for Hawkins et al.'s (1979) study fit the empirical ones extremely well. The present goodness-of-fit equals what we obtained previously in our simulations with the response-selection bottleneck model (cf. Figure 18, top panel). This is because both models treat Task 1 in the same way, using the same Task 1 production rules and high Task 1 priority. Nevertheless, crucial differences between these models become apparent when simulated and empirical mean Task 2 RTs are examined further.

Simulated mean RTs for Task 2. Simulated mean Task 2 RTs (small circles and triangles on dashed curves) from the preliminary SRD model appear in Panel A of Figure 19 along with corresponding empirical mean Task 2 RTs (large circles and triangles on solid PRP curves) from Hawkins et al. (1979). Compared to what the bottleneck model produced (cf. Figure 18, bottom panel), the fit obtained here is markedly better ($R^2 = .968$; RMSE = 43 ms). The preliminary SRD model yields a substantial interaction between the effects of SOA and Task 2 response-selection difficulty; the difficulty effect on simulated mean Task 2 RTs is much less at the short SOAs than at the longer ones, just as Hawkins et al. (1979) found. This interaction stems directly from concurrent response selection being enabled for Task 1 and Task 2 at short SOAs. Thus, we now have strong grounds on which to prefer the SRD model over the response-selection bottleneck model.

Yet the simulated Task 2 RTs from our preliminary version of the SRD model do not fit the empirical Task 2 RTs in all respects. Instead, inspection of Figure 19 (Panel A) reveals several noticeable discrepancies, each substantially greater than the standard errors of the empirical mean RTs. First, the simulated mean RTs at the longest (1200 ms) SOA exceed the corresponding empirical ones by about 100 ms. Second, at the intermediate (600 ms) SOA, exactly the reverse relation holds when Task 2 is difficult; here the simulated mean Task 2 RT underestimates the corresponding empirical one by about 100 ms. Third, at the shorter SOAs, the response-selection difficulty effect on the simulated mean Task 2 RTs is even less than on the empirical RTs.

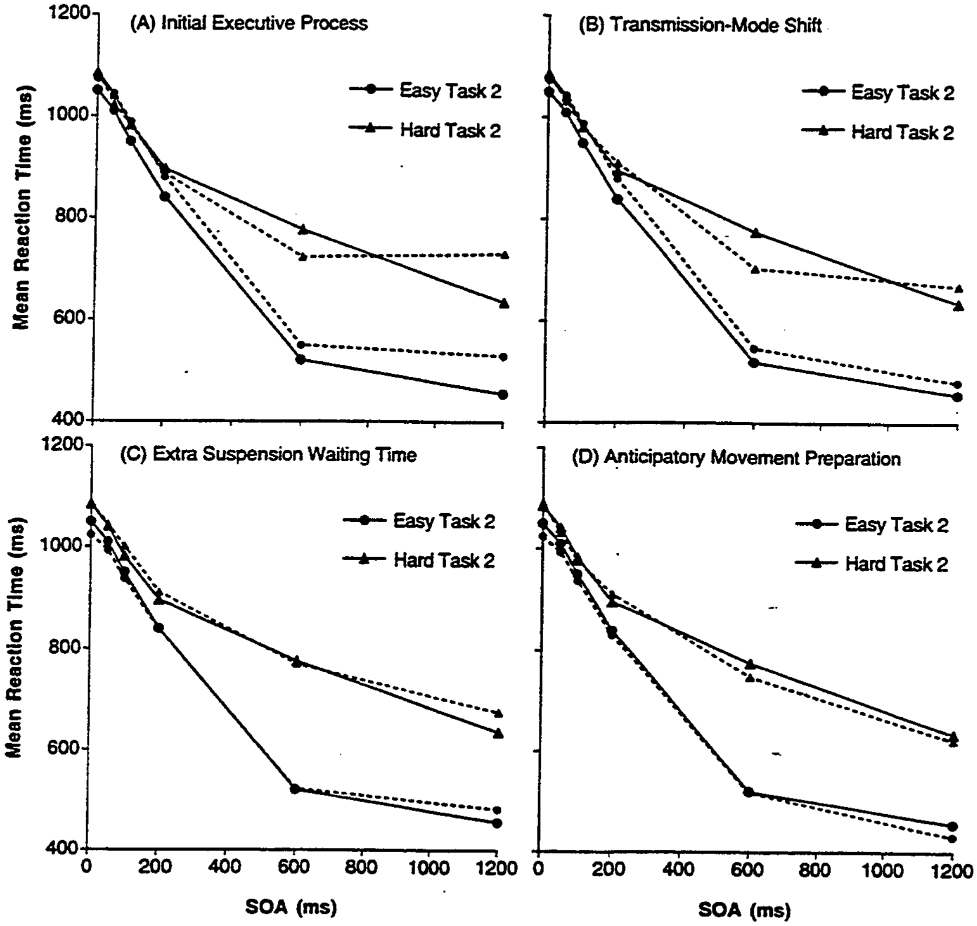

Figure 19. Results from simulations with successively refined versions of the SRD model for Hawkins et al.'s (1979) PRP study involving an auditory-manual Task 1 and visual-manual Task 2. Large symbols on solid curves denote empirical mean Task 2 RTs; small symbols on dashed curves denote simulated mean Task 2 RTs. Circles and triangles represent RTs when Task 2 response selection was respectively easy and hard. Panel A: Goodness-of-fit produced by an initial executive process that enables temporal overlap between response-selection processes for Tasks 1 and 2, but does not incorporate other types of optimization (e.g., deferred-to-immediate transmission-mode shift, suspension waiting time, and anticipatory movement-feature preparation). Panel B: Goodness-of-fit produced by an augmented executive process that both enables concurrent response-selection processes and makes a deferred-to-immediate transmission-mode shift for Task 2 after Task 1 is declared "done." The mode shift significantly improves the fit between simulated and empirical mean Task 2 RTs at the longest (1200 ms) SOA (cf. Panel A). Panel C: Goodness-of-fit produced by a further augmented executive process that adds a suspension waiting time as part of the shift from deferred to immediate response-transmission mode for Task 2. The added suspension waiting time significantly improves the fit between simulated and empirical mean Task 2 RTs at the intermediate (600 ms) SOA (cf. Panel B). Panel D: Goodness-of-fit produced by a final executive process that includes all previous types of optimization plus anticipatory movement-feature preparation for Task 2 responses after Task 1 is declared "done". Such preparation significantly improves the fit between simulated and empirical mean Task 2 RTs at the longest (1200 ms) SOA (cf. Panel C).

Theoretical implications. The relationships between the empirical and simulated mean Task 2 RTs in Panel A of Figure 19 suggest that our preliminary SRD model provides a step in the right theoretical direction. Enabling concurrent response selection for Tasks 1 and 2 lets us account better for the observed interaction between SOA and Task 2 response-selection difficulty effects. However, remaining discrepancies imply that the model needs refinement, which involves adding more features to its initial partially-optimized executive process.

Refinement of Preliminary SRD Model

To confirm the utility of these added optimization features, we have conducted more simulations with several augmented versions of the preliminary SRD model. Along the way, its executive process has been progressively refined. These refinements involve: (a) shifting the production rules for Task 2 from deferred to immediate response-transmission mode while Task 2 is being unlocked; (b) inserting additional ocular-orientation and suspension waiting times; (c) preparing movement features in advance for Task 2 responses after Task 2 has been resumed in immediate mode. Interestingly, each of these refinements improves a particular aspect of the fit between simulated and empirical mean Task 2 RTs for the PRP study by Hawkins et al. (1979).

Contribution of response-transmission mode shift. Panel B of Figure 19 shows what happens when a shift of the response-transmission mode for Task 2 is added to the SRD model's executive process. The discrepancy between simulated and empirical mean Task 2 RTs decreases noticeably at the longest SOA (cf. Figure 19, Panel A). This occurs because if a relatively long SOA is combined with the added mode-shifting capability, then the executive process has enough time to shift the Task 2 production rules to the immediate mode, so selected Task 2 responses may then go directly to their motor processor without taking an extra step through working memory.

Nevertheless, the deferred-to-immediate mode shift for Task 2 does not eliminate all discrepancies between theory and data. In particular, the simulated mean Task 2 RTs are still too large at the longest SOA, whereas at the intermediate (600 ms) SOA, they are too small when Task 2 is difficult (Figure 19, Panel B). This suggests that the executive process of the SRD model requires further refinements.

Contribution of suspension waiting time and increased ocular-orientation time. The necessary refinements involve augmenting the executive process with a brief suspension waiting time at the end of its Task 2 transmission-mode shift. As mentioned already, the suspension waiting time gives Task 1 responses more opportunity to emerge before Task 2 response selection is resumed in the immediate response-transmission mode. Complementing this refinement, we have also modified the preliminary SRD model's executive process so that it can optionally wait a bit longer before moving EPIC's eyes into position for looking at visual Task 2 stimuli.

On the basis of these improvements, a new simulation yields the results shown in Panel C of Figure 19. Here, unlike before (cf. Figure 19, Panel B), the simulated mean Task 2 RTs closely approximate the corresponding empirical ones at all short and intermediate SOAs. In particular, adding the suspension waiting time raises the simulated mean Task 2 RT at the intermediate (600 ms) SOA when Task 2 is difficult. Also, adding the ocular-orientation time slightly increases the selection-difficulty effect at the shorter SOAs. Thus, the only significant remaining discrepancy between simulated and empirical Task 2 RTs is at the longest (1200 ms) SOA, where the refined SRD model still yields Task 2 responses that are consistently too slow.

Contribution of anticipatory movement-feature preparation. To eliminate this last discrepancy, and to justify one more refinement of the preliminary SRD model, its executive process may be augmented with anticipatory movement-feature preparation. This involves having the executive process instruct EPIC's motor processors to prepare, in advance, some of the movement features needed for producing subsequently selected Task 2 responses. Specifically, for Task 2 of the PRP study by Hawkins et al. (1979), the executive process would prepare a right-hand movement feature after completing Task 1, since Task 2 always requires right-hand responses. Such anticipatory preparation would occur if and only if Task 2 response selection is not already underway when the executive process begins unlocking Task 2.

Results obtained from a new simulation that includes this last refinement appear in Panel D of Figure 19. Anticipatory movement-feature preparation, coupled with other executive-optimization features, yields simulated mean Task 2 RTs that closely fit Hawkins et al.'s (1979) empirical mean Task 2 RTs at all SOAs. In particular, a closer fit between theory and data emerges at the longest (1200 ms) SOA, where the SRD model's executive process now has enough time to complete its final preparatory activities.

Numerical parameter values. Table 4 (Column Aud/Man) shows numerical values that we assigned to the means of the context-dependent parameters for the fully-refined SRD model to produce the simulated mean RTs in Panel D of Figure 19. Two of these parameters -- the mean number of Task 2 selection cycles, and the suspension waiting time -- depend on the Task 2 response-selection difficulty. However, as anticipated already, most other parameters (e.g., mean stimulus-identification times, response transduction times, unlocking-onset latency, etc.) stay the same regardless of Task 2 response-selection difficulty. The means of the previous context-independent parameters (Table 2) also stay the same. Thus, the SRD model uses relatively few degrees of freedom in accounting for the main and interactive effects of SOA and response-selection difficulty.

Theoretical implications. In conclusion, it appears that each feature of the SRD model's optimized executive process helps account for salient aspects of data from the PRP procedure. The temporal overlap of response-selection processes for Tasks 1 and 2, together with deferred-mode response transmission for Task 2, provides an enhanced account of interactions between SOA and response-selection difficulty effects on mean Task 2 RTs. A deferred-to-immediate mode shift, together with subsequent anticipatory movement-feature preparation, further improves the fit between simulated and empirical mean Task 2 RTs at long SOAs. Similarly, the suspension waiting time that accompanies this mode shift improves the fit at intermediate SOAs, as does the ocular-orientation time at short SOAs. When these optimization features are combined, the fully-refined SRD model yields an excellent fit to the data. It accounts for most of the systematic variance ($R^2 = .997$; RMSE = 14 ms) in the empirical mean RTs from Hawkins et al.'s (1979) PRP study with an auditory-manual Task 1 and visual-manual Task 2.

Degrees of Freedom for The SRD Model

Of course, the goodness-of-fit achieved by our initial simulations with the SRD model for the PRP study by Hawkins et al. (1979) raises an intriguing question. How many degrees of freedom does the model typically have to account for empirical PRP curves of mean Task 2 RTs? Do the degrees of freedom used by the model exceed those associated with systematic variance in the data? In answer to these questions, we may look again at the protoype theoretical PRP curve that is generated by the model when its parameters are constants.

Prototype PRP Curve and Degrees of Freedom

As Figure 14 illustrates, the prototype PRP curve contains five distinct linear segments. According to previous equations and inequalities (Table 3), the quantitative properties of these segments stem from five degrees of freedom in the SRD model, assuming that certain parameters (e.g., Task 1 stimulus identification, response selection, and response transduction times) are preset on other bases. The present five degrees of freedom are associated respectively with the unlocking-onset latency, suspension waiting time, Task 2 response-selection time, Task 2 stimulus-identification time, and preparation waiting time. To be specific, the unlocking-onset latency determines the length of the prototype curve's left-most diagonal segment, which involves post-selection slack. The suspension waiting time and Task 2 response-selection time respectively determine the height and width of the upper-left horizontal segment, which involves mid-selection slack. Similarly, the suspension waiting time determines the extent of the middle diagonal segment, which involves pre-selection slack. The sum of the stimulus-identification and response-selection times for Task 2 determine the height of the next-to-right horizontal segment (neutral baseline).

Table 4

Context-Dependent Parameters in Simulations Conducted with the SRD Model for The PRP Study by Hawkins et al. (1979)

System Component	Parameter Name	Task 2 Difficulty	Mean Parameter Values in Each Condition Aud/Man	Aud/Voc	Vis/Voc	Vis/Man
perceptual processors	auditory identification time	easy & hard	335	335	335	335
	visual identification time	easy & hard	245	245	245	245
Task 1 process	number of selection cycles	easy & hard	2.25	2.25	2.25	2.25
Task 2 process	number of selection cycles	easy	1.00	1.00	1.00	1.00
		hard	5.00	5.00	5.00	5.00
	preparation benefit	easy & hard	50	50	50	50
executive process	ocular orientation time	easy & hard	185	235	335	335
	unlocking onset latency	easy & hard	300	250	200	0
	suspension waiting time	easy	0	100	50	0
		hard	100	50	0	0
	preparation waiting time	easy & hard	435	1200	545	485
apparatus	manual transduction time	easy & hard	10	10	10	10
	vocal transduction time	easy & hard	120	120	120	120

Note. Time parameters are given in milliseconds. "Easy" and "hard" refer to the difficulty of response selection in Task 2. "Aud" and "Vis" refer to the modality of Task 1 stimuli in each condition (auditory or visual); "Voc" and "Man" refer to the modality of Task 1 responses in each condition (vocal or manual).

The width of this latter segment is determined by the preparation waiting time. All other quantitative features of the prototype curve depend on parameters that are either fixed (i.e., not context dependent) or inseparable (i.e., not "identifiable") from already mentioned ones.[31]

In addition to the five degrees of freedom just mentioned, the SRD model has one more, which is associated with the ocular-orientation time. Under conditions that lead this parameter to have relatively large positive magnitudes, it may supercede the unlocking-onset latency to govern the height and extent of the prototype PRP curve's left-most linear segment (Table 3 and Panel B of Figure 15). Thus, overall, the SRD model has six degrees of freedom with which to account for an individual observed PRP curve of empirical mean Task 2 RTs.

Assessment of Initial Simulation Results

Applying this degrees-of-freedom analysis, we may further assess the goodness-of-fit achieved in Panel D of Figure 19, which comes from our initial simulation with the fully-refined SRD model for the Task 2 PRP curves of the Auditory-Manual Task 1 condition in Hawkins et al. (1979). As our analysis shows, the SRD model actually uses eight degrees of freedom to account for these curves across the two levels of Task 2 response-selection difficulty and six levels of SOA included there. Six of the eight degrees of freedom, corresponding to the six previously mentioned parameters (i.e., ocular-orientation time, unlocking-onset latency, suspension waiting time, Task 2 stimulus-identification time, Task 2 response-selection time, and preparation waiting time) govern the fit to the PRP curve from the "easy" condition. Some of the same parameters (i.e., ocular-orientation time, unlocking-onset latency, stimulus-identification time, response-transduction time) and degrees of freedom likewise govern the fit to the PRP curve from the "hard" condition, because they have the same numerical values regardless of response-selection difficulty (Table 4, Column Aud/Man). In addition, two more degrees of freedom are used to help fit the PRP curve from the "hard" condition; they correspond to adjusting the mean suspension waiting time and mean number of selection cycles, which influences the Task 2 response-selection times as a function of response-selection difficulty. In contrast, there are twelve degrees of freedom among the present empirical Task 2 PRP curves, due to the orthogonal combination of six SOAs and two levels of response-selection difficulty ("easy" vs. "hard"). Thus, in order to produce an excellent fit between simulated and empirical mean Task 2 RTs, the SRD model requires significantly fewer degrees of freedom than the data contain (8 vs. 12).

Indeed, as discussed more fully later, such considerations suggest that the fit produced by the SRD model between theory and data is nearly ideal. By "ideal" we mean that the model accounts for essentially all of the statistically reliable variance in the empirical mean Task 2 RTs, and while doing so, the model uses no more degrees of freedom than are warranted by the known reliable factor effects on these RTs. With respect to the latter criteria for success, it would therefore be difficult to improve upon the account that the SRD model provides. The model seems no more nor less systematically complex than the data and subjects' performance are.

Further Simulations for Various Stimulus-Response Modalities

The preceding positive assessment of the SRD model and its EPIC architecture may be generalized to cases involving other stimulus and response modalities. In addition to having a Task 1 with manual responses to auditory stimuli, the PRP study by Hawkins et al. (1979) included

[31] For example, the height of the prototype curve's upper-left horizontal segment above the neutral baseline equals the sum of the suspension waiting time and minimum unlocking duration. We take the minimum unlocking duration to be a context-independent parameter whose mean always equals 100 ms (Table 2), so only the suspension waiting time is free to govern this segment's height. Similarly, the sum of the Task 2 stimulus-identification and response-transduction times contribute to the height of the next-to-right horizontal segment (neutral baseline). However, the response-transduction time is not generally separable from the stimulus-identification time, so the response-transduction time must be preset on other a priori grounds, leaving only the stimulus-identification time as a degree of freedom.

several further interesting conditions. They orthogonally varied whether the Task 1 stimulus modality was auditory or visual, and whether the Task 1 response modality was manual or vocal. As before, however, the Task 2 stimuli and responses were always visual and manual, respectively, with two levels of Task 2 response-selection difficulty. This enables a thorough examination of how Task 1 and Task 2 factors combine to influence multiple-task performance within a constant Task 2 context.

For example, we can use the further conditions from Hawkins et al.'s (1979) study to evaluate one of our important theoretical claims: if neither the perceptual nor motor requirements of Task 2 conflict with those of Task 1, then Task 2 RTs may contain post-selection slack, and PRP curves produced by the SRD model may closely fit empirical PRP curves because they come from Family 1, where the effects of SOA and Task 2 response-selection difficulty interact significantly with each other (Figure 15, Panel A). Also, we can examine how well the SRD model accounts for PRP curves when the two tasks do conflict in that they both involve visual stimuli and require eye movements to different spatial locations. If the model is correct, then under the latter conditions, eye movements may preclude post-selection slack during Task 2, so simulated and empirical PRP curves may come from Family 2 or 3, where the SOA and Task 2 response-selection difficulty have additive effects (Figure 15, Panels B and C). In what follows, these theoretical prospects are pursued through simulations for the auditory-vocal, visual-vocal, and visual-manual versions of Task 1 that Hawkins et al. (1979) combined with their visual-manual Task 2.

Auditory-Vocal Task 1

The procedure for Hawkins et al.'s (1979) auditory-vocal Task 1 was the same as for their previous auditory-manual Task 1, except that subjects produced the words "red" and "green" vocally in response to low and high tones, respectively, rather than making manual keypresses. After SOAs like those used before, the visual Task 2 stimuli (i.e., numerals) appeared, and subjects again made right-hand manual keypress responses to them. There were either two or eight alternative S-R pairs during Task 2, as in prior conditions.

Empirical mean RTs. Figure 20 (Panel A) shows the empirical mean RTs (solid curves) obtained by Hawkins et al. (1979) when the auditory-vocal Task 1 was combined with the visual-manual Task 2. On average, Task 1 RTs are somewhat longer here than when Task 1 required manual responses (740 ms vs. 630 ms). Also, the mean Task 1 RTs tend to be slightly longer when Task 2 is relatively difficult. However, this difficulty effect is small (under 30 ms), and the mean Task 1 RTs do not vary systematically with SOA. Thus, except for the Task 1 RT increase caused by switching to the vocal response modality, the present pattern of mean Task 1 RTs replicates what Hawkins et al. (1979) obtained with their auditory-manual Task 1.

Similarly, the empirical mean Task 2 RTs look much like prior ones. They are affected substantially by the SOA, which yields sharply declining PRP curves. Also, response-selection difficulty (two vs. eight S-R pairs) has a substantial effect (130 ms) on them at long SOAs. Yet at the shortest SOA, the difficulty effect (75 ms) is significantly attenuated, manifesting a marked SOA-by-difficulty interaction, as occurred previously with an auditory-manual Task 1. Again, the empirical PRP curves appear as if they might have stemmed from intermixing Families 1 and 2 of the SRD model.

Details of simulation. To account for these results, we have conducted more simulations with the SRD model. Here the model's executive process used the same production rules as before, and many of the numerical parameter values stayed the same (Table 4, Column Aud/Voc). For example, the means of the auditory and visual stimulus-identification times, response-selection times, and movement-production times did not change. Instead, the most important new addition was simply that vocal responses were involved and had a somewhat longer transduction time than manual responses did (120 vs. 10 ms).

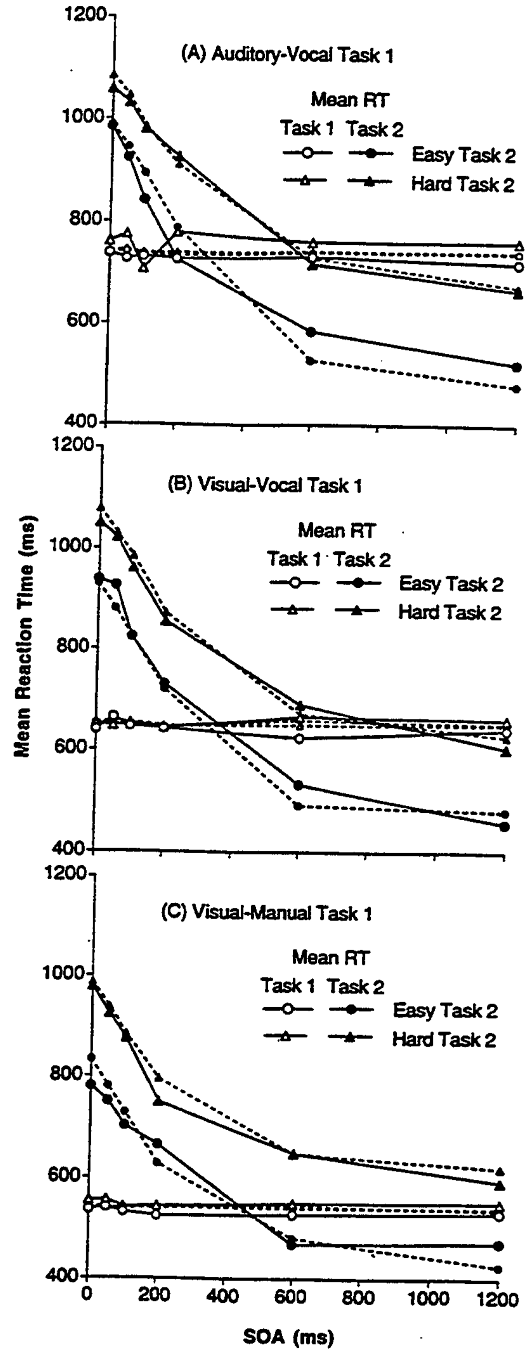

Figure 20. Results from simulations with the SRD model for further conditions of Hawkins et al.'s (1979) PRP study. Large symbols on solid curves denote empirical mean RTs; small symbols on dashed curves denote simulated mean RTs. Filled circles and triangles represent Task 2 RTs when response-selection in Task 2 was respectively easy or hard; unfilled circles and triangles represent corresponding Task 1 RTs. Panel A: Simulated versus empirical mean RTs in an auditory-vocal Task 1 combined with a visual-manual Task 2. Panel B: Simulated versus empirical mean RTs in a visual-vocal Task 1 combined with a visual-manual Task 2. Panel C: Simulated versus empirical mean RTs in a visual-manual Task 1 combined with a visual-manual Task 2.

This assumed difference in transduction times for the vocal and manual response modalities has several justifications. Articulatory movements may begin significantly before their resultant sounds are physically detectable (Ladefoged, 1975). Such differential onsets would account for why vocal Task 1 RTs were longer than manual ones in Hawkins et al.'s (1979) study. Also, if the vocal RT increase stems from a late peripheral source, then it could account for why the Task 2 RTs were not correspondingly longer compared to what happened when Task 1 required manual responses. The Task 2 RTs should remain virtually unchanged, because the executive process typically starts unlocking Task 2 soon after early internal events (action initiation) associated with Task 1 being "done," rather than after late external events involving physical response transduction.

Simulated mean RTs. In light of these considerations, Figure 20 (Panel A) shows simulated mean RTs (dashed curves) produced by the SRD model for Hawkins et al.'s (1979) study with an auditory-vocal Task 1. Here the fit between the simulated and empirical mean Task 1 RTs is again at least moderately good (RMSE = 21 ms). There is also at least a moderately good fit ($R^2 = .976$; RMSE = 34 ms) between the simulated and empirical mean Task 2 RTs. In particular, the simulated mean Task 2 RTs faithfully mimic the observed interaction between SOA and Task 2 response-selection difficulty. Of course, this is what we would expect when the stimulus modalities of Tasks 1 and 2 allow response-selection processes for the two tasks to overlap temporally, yielding post-selection slack in Task 2 RTs and PRP curves from Family 1 of the SRD model.

Nevertheless, some discrepancies between the present simulated and empirical mean Task 2 RTs are noticably greater than those in our previous simulations for the auditory-manual Task 1 (cf. Figure 19, Panel D). To be specific, consider what happens when Task 2 involves two S-R pairs and the SOA is "very short" ($0 < \text{SOA} \leq 200$ ms). Under such circumstances, the simulated mean Task 2 RTs exceed the empirical mean Task 2 RTs by 50 ms or more. This occurs because the empirical mean Task 2 RTs decline more steeply (slope = -1.3) than do the simulated ones (slope = -1.0) over the interval of "very short" SOAs.

There are also other discrepancies between the simulated and empirical mean Task 2 RTs at longer SOAs (i.e., SOA = 600 and 1200 ms) when Task 2 is easy. In these cases, the simulated RTs fall below the empirical ones by about 50 ms. This excessive drop happens despite the simulated Task 2 RTs having a shallower slope than the empirical Task 2 RTs do at "very short" SOAs.

Theoretical implications. Although their absolute magnitudes are not great, the preceding discrepancies significantly exceed the 10 ms standard errors of the empirical mean Task 2 RTs that accompany the auditory-vocal Task 1. It therefore appears that the SRD model may require some modification (e.g., see Meyer & Kieras, 1997b). Yet the present version of the model has much to offer us; thus far, its account for Hawkins et al.'s (1979) data is much better than other extant theoretical alternatives could achieve. Furthermore, as we discuss next, the SRD model's success extends to conditions involving a visual-vocal Task 1.

Visual-Vocal Task 1

The procedure for Hawkins et al.'s (1979) visual-vocal Task 1 was the same as for their previous auditory-vocal Task 1, except that the Task 1 stimuli were letters ("H" and "N") displayed at a different spatial location than the visual Task 2 stimuli. In response to the Task 1 stimuli, subjects again said the words "red" and "green," respectively. The responses to the Task 2 stimuli (digits), which involved two or eight S-R pairs, were right-hand manual keypresses.

Because the stimuli in Tasks 1 and 2 were spatially separated, they could not both be foveated at the same time. Instead, subjects had to look first at the Task 1 stimulus and second at the Task 2 stimulus, making a saccadic eye movement between the locations of the two stimuli. This requirement presumably delayed the start of response selection for Task 2 relative to what happened when Task 1 was auditory and subjects moved their eyes to the Task 2 stimulus location relatively early. By replacing the auditory Task 1 with a visual Task 1, Hawkins et al. (1979) may have eliminated post-selection slack in the Task 2 RTs at short SOAs, which would yield PRP curves from Family 2 or 3 of the SRD model (Figure 15, Panels B and C). As mentioned already, such curves would embody additive rather than interactive effects of SOA and response-selection difficulty on Task 2 RTs.

Empirical mean RTs. Consistent with the latter expectation, Figure 20 (Panel B) shows empirical mean RTs (solid curves) obtained by Hawkins et al. (1979) when their visual-vocal Task 1 was combined with the visual-manual Task 2. Here both the SOA and Task 2 response-selection difficulty affect the mean Task 2 RTs substantially; these effects are nearly additive and associated with approximately "parallel" PRP curves. In contrast, neither the SOA nor Task 2 difficulty affect the mean Task 1 RTs much at all. On average, the empirical mean Task 1 RTs are about 110 ms less than those in the prior auditory-vocal Task 1 (cf. Figure 20, Panel A), suggesting that subjects identified the visual Task 1 stimuli more quickly than they did the previous auditory Task 1 stimuli. As our subsequent simulations indicate, these results are consistent with the SRD model, which provides a good quantitative fit to the data.

Details of simulation. To account for Hawkins et al.'s (1979) results from the combination of visual-vocal Task 1 and visual-manual Task 2, we have applied the SRD model in the same way as before, using its standard executive and task processes. Again, many of the model's parameters had mean values (Table 4, Column Vis/Voc) like those during previous simulations. For example, we assume that after the stimuli for Tasks 1 and 2 are foveated, the process of identifying them took the same amounts of time in both tasks. Similarly, the assumed transduction times for the manual and vocal responses are the same as before.

However, an important change had to be made in one key parameter when Task 1 was visual. We increased the ocular-orientation time (t_{o2}) for Task 2, which corresponds to the time at which EPIC's eyes first fixate the Task 2 stimulus location after the onset of the Task 1 stimulus. The mean value of t_{o2} is determined by having the SRD model's executive process request an eye movement from the Task 1 stimulus location to the Task 2 stimulus location immediately after the onset of the Task 1 stimulus has been detected. Thus, when the SOA equaled zero, the process of identifying the visual Task 2 stimulus began about 150 ms later than it had when Task 1-involved auditory stimuli. The start of response selection for Task 2 was also concomitantly delayed at short SOAs, precluding it from temporally overlapping with response selection for Task 1.

Simulated mean RTs. The dashed curves in Figure 20 (Panel B) show the simulated mean RTs that resulted from these parameter changes. For Task 1, the fit between the simulated and empirical mean Task 1 RTs is again reasonably good (RMSE = 14 ms). Similarly, the SRD model accounts at least moderately well ($R^2 = .984$; RMSE = 24 ms) for the mean Task 2 RTs. It successfully mimicked the approximate additivity between the effects of SOA and Task 2 response-selection difficulty; the difficulty effects on simulated mean Task 2 RTs are about the same at short and long SOAs, because little or no post-selection slack occurs in Task 2 regardless of the SOA. Indeed, the simulated PRP curves appear as if they are a mixture of ones from the model's Family 2 or 3. Neither the simulated nor empirical PRP curves diverge as much here as when Task 1 involved auditory stimuli (cf. Panel A of Figure 20, and Panel D of Figure 19). This is what we would expect, given our previous analysis of the consequences that long ocular-orientation times may have.

Theoretical implications. The present simulation documents the ability of the SRD model to account for various quantitative patterns of PRP curves, depending on particular parameter values that a multiple-task situation entails. As anticipated in prior discussion, it is not necessary to assume a response-selection bottleneck just because empirical PRP curves exhibit additive SOA and response-selection difficulty effects. Rather, such additivity may arise from peripheral perceptual-motor bottlenecks that impede what would otherwise be concurrent response-selection processes. Further reinforcing these conclusions, we have simulated results from a fourth set of conditions in the PRP study by Hawkins et al. (1979).

Visual-Manual Task 1

Hawkins et al.'s (1979) fourth set of conditions involved two visual-manual tasks. Here Task 1 required manual left-hand keypresses in response to visual letters, and Task 2 required manual right-hand keypresses in response to visual digits. The stimuli in Tasks 1 and 2 were spatially separated as in the previous case with a visual-vocal Task 1. Thus, one might expect eye movements between the stimuli's spatial locations to play an important role again, yielding PRP curves similar to those observed earlier. Also of interest now are additional phenomena that stem from both tasks requiring the same (i.e., manual) motor processor.

Empirical mean RTs. Figure 20 (Panel C) shows the empirical mean RTs that Hawkins et al. (1979) obtained for the two visual-manual tasks. Again the mean Task 1 RTs are virtually constant as a function of the SOA and Task 2 response-selection difficulty. Yet both the SOA and Task 2 response-selection difficulty affect the empirical mean Task 2 RTs reliably. These latter effects are approximately additive, yielding nearly parallel PRP curves, just as when subjects performed a visual-vocal Task 1 (cf. Figure 20, Panel B).

Suprisingly, though, the visual-manual Task 1 yielded smaller PRP effects than did the other primary tasks. At zero SOA, for example, the PRP effect induced by the visual-manual Task 1 was only 346 ms on average, whereas the previous auditory-vocal Task 1 induced a mean PRP effect of 427 ms. Such a reduction seems counterintuitive because when the visual-manual Task 1 is combined with the visual-manual Task 2, it creates potential conflicts between tasks in both the perceptual and motor stages of processing. However, despite these conflicts, the visual-manual Task 1 actually interfered least with the visual-manual Task 2. This is difficult to explain in terms of simple bottleneck models. Nevertheless, through its optimized task scheduling and detailed treatment of perceptual-motor processes, the SRD model accounts well for the present observations.

Details of simulation. Our simulation of results from Hawkins et al.'s (1979) combination of two visual-manual tasks applied the SRD model with many of the same parameter values as before (Table 4, Column Vis/Man). Relatively long ocular-orientation times were used again for Task 2, given that eye movements had to be made from the Task 1 stimulus location to the Task 2 stimulus location after the Task 1 stimulus onset was detected. However, in order to produce a close fit between theory and data, the mean of one important parameter had to be changed. We decreased the unlocking-onset latency of the SRD model's executive process. Given this decrease, the executive process begins unlocking Task 2 as soon as the Task 1 response identity is selected, thus decreasing how long Task 2 is delayed before proceeding to completion. As indicated previously, such early unlocking may yield simulated PRP curves that come from Family 4, reducing the PRP effect (Figure 15, Panel D).

The early unlocking assumed here has a straightforward rationale; it follows directly from efficient optimized task scheduling by the SRD model's executive process. Under present conditions, the times taken for stimulus identification, response selection, movement production, and response transduction are all presumably rather short during the visual-manual Task 1. Furthermore, at short SOAs, the start of Task 2 stimulus identification is delayed by the long ocular-orientation time that precedes it. Following this delay, the times taken for stimulus identification, response selection, movement production, and response transduction during Task 2 must all be at least as long as those for Task 1, because Task 2 is visual-manual like Task 1, and Task 2 never involves fewer S-R pairs than Task 1 does. Such constraints together guarantee that overt Task 2 responses can never occur before Task 1 responses, even if Task 2 always proceeds from start to finish in the immediate response-transmission mode. Thus, the executive process may unlock Task 2 relatively early in this case.

Simulated mean RTs. The aptness of the latter rationale is documented by the dashed curves in Figure 20 (Panel C), which show simulated mean RTs that the SRD model produced for Hawkins et al.'s (1979) combination of two visual-manual tasks. There is a good fit between the simulated and empirical mean Task 1 RTs (RMSE = 11 ms). Although not quite as good, the fit between the simulated and empirical mean Task 2 RTs is at least somewhat encouraging ($R^2 = .975$; RMSE = 31 ms). Again successfully mimicked are the observed additive effects of the SOA and Task 2 response-selection difficulty, yielding approximately parallel simulated PRP curves, as expected from the long ocular-orientation times and absence of post-selection slack. Likewise successfully mimicked are the relatively small PRP effects at zero SOA, which stem from the early unlocking of Task 2.

Theoretical implications. Through our simulations for the visual-manual tasks of Hawkins et al. (1979), two important conceptual claims have been upheld. First, we have again shown that long ocular-orientation times may lead to PRP curves with additive effects of SOA and Task 2 response-selection difficulty. Second, it is now evident that small PRP effects may indeed stem from short unlocking-onset latencies, which are used when rapid Task 1 processes already ensure against premature Task 2 responses. Apparently human subjects -- like the executive processes of the SRD model -- can adjust their task-scheduling strategies flexibly, thereby satisfying standard instructions for the PRP procedure while attaining shorter Task 2 RTs than would otherwise be possible.

Overall Goodness-of-Fit and Degrees of Freedom

In summary, Figure 21 depicts the overall goodness-of-fit that the SRD model has achieved for mean Task 2 RTs from the PRP study by Hawkins et al. (1979). Across the various conditions of this study, there are forty-eight pairs of corresponding empirical and simulated mean Task 2 RTs, which come from orthogonally combining six SOAs, two Task 1 stimulus modalities (auditory and visual), two Task 1 response modalities (vocal and manual), and two levels of Task 2 response-selection difficulty (easy and hard). On balance, the fit between theory and data seems reasonably satisfactory ($R^2 = .984$; RMSE = 27 ms).[32] It is certainly better than could be achieved by most, if not all, extant bottleneck models and resource theories of human multiple-task performance.

To justify the preceding assessment more fully, we need some further criteria for evaluating the goodness-of-fit between theory and data. These criteria are provided by principles based on the analysis of variance (ANOVA; Weiner, 1962). According to ANOVA principles, the forty-eight empirical mean Task 2 RTs in Figure 21 each differ more or less from their grand mean (i.e., the overall arithmetic average), yielding a *total variance* for this data set. Part of the total variance is *systematic*; it involves statistically reliable mean-RT differences that occurred through main effects and interactions of Hawkins et al.'s (1979) independent variables. The remainder of the total variance (i.e., total variance - systematic variance) is *noise*; it involves unreliable mean-RT differences. Furthermore, there are forty-seven degrees of freedom (df) associated with the total variance (i.e., the forty-eight mean Task 2 RTs embody forty-seven independent differences about their grand mean). Among the total variance's degrees of freedom, some belong to the systematic variance, and the rest belong to the noise (i.e., total df = systematic df + noise df). Specifically, for each degree of freedom that the systematic variance has, there is a distinct linear contrast that can be formed from the empirical mean Task 2 RTs and that has a reliable positive or negative value. The systematic variance's degrees of freedom place an upper bound on how many different parameter values are needed to account for the systematic variance. A successful theoretical model should therefore satisfy two criteria: First, it ought to account for all of the systematic variance and none of the noise in the data; one wants to characterize exactly why and how the independent variables have their reliable effects on the dependent variable. Second, in accounting for the systematic variance, the model ought to use "free" (i.e., adjustable) parameter values whose total number is less than or equal the systematic variance's degrees of freedom; this makes the model's account be relatively parsimonius.

With respect to the latter criteria, the SRD model succeeds well at accounting for the empirical mean Task 2 RTs from the study by Hawkins et al. (1979). ANOVA reveals that 99.9% of the total variance among these RTs was systematic; the systematic variance has 30 df. Correspondingly, the model's simulated mean Task 2 RTs account for 98.4% of the systematic variance and none of the noise. Along the way, the model uses twenty-seven adjustable (context dependent) parameter values (Table 5). However, only twenty-two of these values have been estimated from the empirical mean Task 2 RTs. Thus, in effect, the adjustable parameters used by the SRD model for its account are markedly fewer in number than the systematic variance's degrees of freedom. The model's success seems about as good as could be achieved by any model under these conditions.

32 The overall goodness-of-fit achieved by the SRD model for the mean Task 1 RTs is likewise reasonably satisfactory (RMSE = 14 ms).

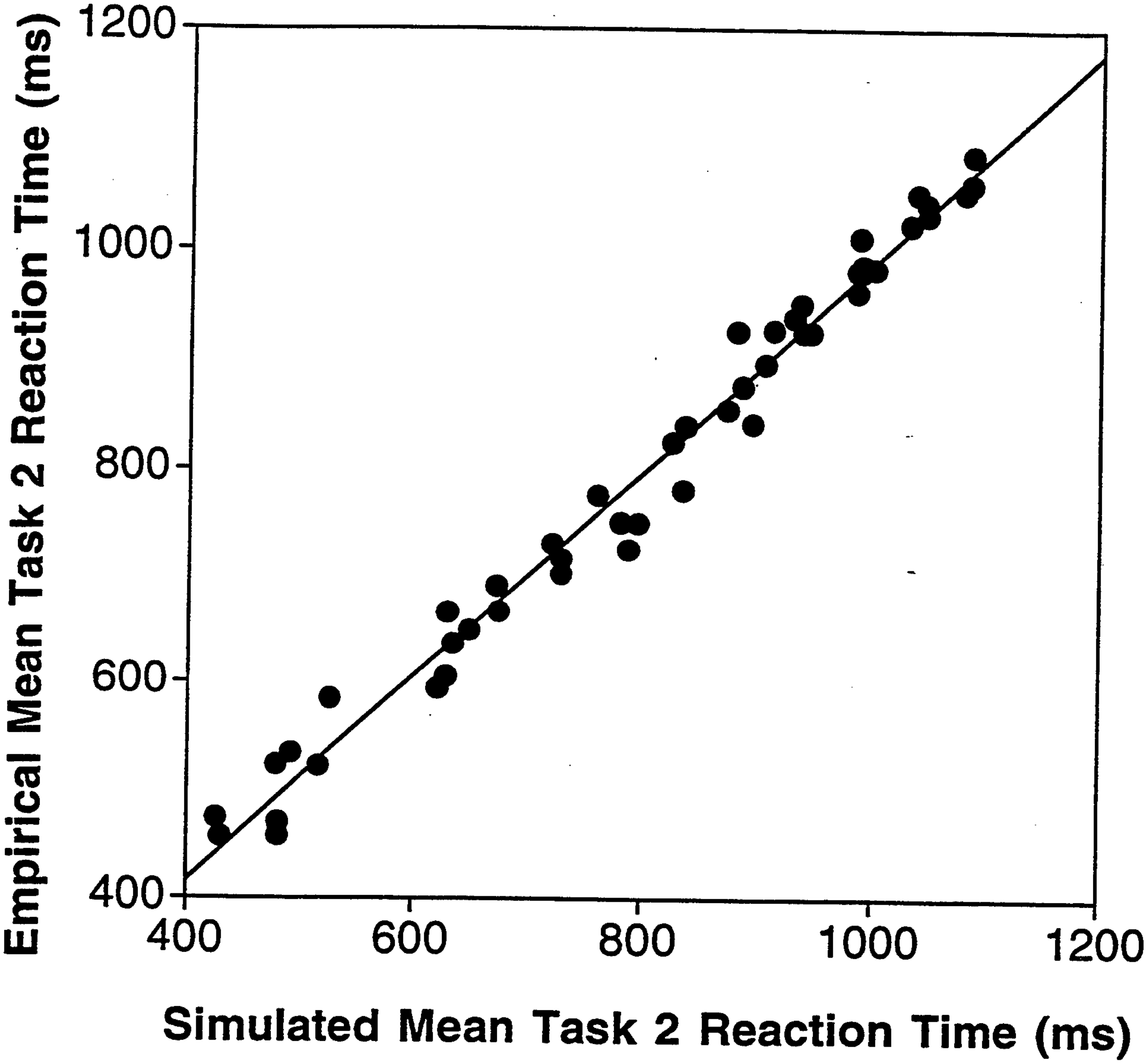

Figure 21. Overall goodness-of-fit between simulated and empirical mean Task 2 RTs for Hawkins et al.'s (1979) study with the PRP procedure. The RTs come from conditions across which there were orthogonal manipulations of Task 1 stimulus modalities (auditory and visual), Task 1 response modalities (manual and vocal), Task 2 response-selection difficulty (easy and hard), and SOA (cf. Figure 20). Using twenty-two adjustable context-dependent parameter values estimated from Task 2 data (Table 5), the SRD model accounts for 98.4% of the systematic (statistically reliable) variance in the forty-eight empirical mean Task 2 RTs.

Table 5

Number of Adjustable Context-Dependent Parameters Used in Simulations With The SRD Model for The PRP Study by Hawkins et al. (1979)

System Component	Parameter Name	Basis for Estimate	No. of Values Estimated
perceptual processors	stimulus identification time	Task 1 RT	2
Task 1 process	number of selection cycles	Task 1 RT	1
Task 2 process	number of selection cycles	Task 2 RT	2
executive process	ocular orientation time	Task 2 RT	4
	unlocking-onset latency	Task 2 RT	4
	suspension waiting time	Task 2 RT	8
	preparation waiting time	Task 2 RT	4
apparatus	response-transduction time	Task 1 RT	2

Note. The number of estimated values (right-most column) refers to how many different means each of the indicated parameters had, depending on which combinations of Task 1 stimulus modality (auditory or visual), Task 1 response modality (vocal or manual), and Task 2 response-selection difficulty (easy or hard) were involved. As the next-to-right column indicates, the means of the parameters were estimated on the basis of either mean Task 1 or Task 2 RTs. For Task 2, which always involved visual stimuli and manual responses, the stimulus-identification and response-transduction times were assigned the same mean values as those for the visual-manual Task 1, which were estimated from the empirical mean Task 1 RTs.

General Discussion

A principal thesis of the present article is that detailed computational modeling can contribute significantly to understanding, characterizing, and predicting human multiple-task performance. To support our thesis, we have formulated the EPIC (Executive-Process/Interactive-Control) architecture, a comprehensive theoretical framework that has software modules for processing information at perceptual, cognitive, and motor levels. With EPIC as its foundation, the SRD (Strategic Response Deferment) model has been introduced and used here in realistic simulations of quantitative results from a basic multiple-task situation, the PRP procedure. This model accounts well for RT data obtained across a variety of conditions in a representative study by Hawkins et al. (1979), whereas other alternatives (e.g., the response-selection bottleneck model) seem less adequate. In a subsequent companion article (Meyer & Kieras, 1997b), we show that the SRD model also accounts well for RT data from several other studies (e.g., Karlin & Kestenbaum, 1968; McCann & Johnston, 1992; Pashler, 1990), including ones with additional combinations of stimulus modalities, response modalities, S-R mappings, and task instructions. Viewed overall, our research helps document the potential utility of the EPIC architecture and computational models based on it.

Theoretical Questions and Answers

Concerning multiple-task performance, application of the SRD model lets us answer several major questions at least tentatively. Is there an immutable "central" (e.g., response selection) bottleneck in the human information-processing system? Why do independent variables such as stimulus-onset asynchrony and response-selection difficulty have effects on secondary-task RTs that are additive under some conditions and interactive under others? What role do eye movements play in modulating observed patterns of RTs across primary and secondary tasks? When concurrent tasks require access to the same rather than different motor mechanisms, does this alter people's strategies for scheduling prior stages of processing? How do people adapt to alternative instructions about which tasks should be primary and secondary? In light of results from our initial simulations, it appears that answers to such questions are attainable and instructive.

We have found no compelling justification yet to assume or infer the existence of an immutable central response-selection bottleneck. On the contrary, our simulations with the SRD model suggest that under at least some representative conditions, subjects' response-selection processes for two concurrent tasks overlap temporally, as if the tasks are performed independently at a procedural cognitive level. When empirical RT data (e.g., additive effects of SOA and response-selection difficulty) suggest otherwise, this may happen because ancillary contextual factors preclude the temporal overlap of response-selection processes. For example, intervening eye movements can preclude such overlap. If the spatial location of an impending visual secondary-task stimulus is uncertain, or if people must move their eyes between visual primary and secondary task stimuli, then response selection for the secondary task may be delayed enough that it does not overlap with response selection for the primary task. Response selection for a secondary task may also be suspended temporarily by executive processes while they shift from a deferred to an immediate response-transmission mode. Behavioral consequences of these latter operations are likely to be salient when the duration of the secondary task is relatively long compared to the primary task's duration. However, this salience should not be taken as evidence of an immutable central bottleneck. A more plausible conclusion is that people have flexible strategies for scheduling various stages of processing to satisfy instructions about task priorities. As a result, bottleneck-like phenomena can emerge when instructions constrain the responses for a secondary task to come after those for a primary task (cf. Koch, 1993, 1994).

Our proposals about alternative response-transmission modes, through which selected responses are either stored temporarily in working memory (deferred mode) or sent directly to their motor processors (immediate mode), likewise open broadened perspectives on multiple-task performance. The efficient use of such transmission modes may explain how people adapt flexibly to various sets of instructions about primary and secondary task priorities while maximally exploiting available information-processing resources. Further simulations beyond the present ones suggest, for example, that subjects' use of the immediate and deferred transmission modes can change beneficially, depending on whether or not subjects have full foreknowledge about the serial order of impending stimuli and responses (Meyer & Kieras, 1997b). This adds a new dimension to the role that working memory might play as part of executive mental control.

In addition, our research highlights the fact that limitations of perceptual/motor mechanisms strongly shape human multiple-task performance. Although no definitive evidence of a central response-selection bottleneck has yet emerged, one or more peripheral bottlenecks perhaps exist at the level of movement production (cf. Keele, 1973). An illustrative case of this is the unitary manual motor processor that we have assumed for preparing and executing movements by each of the two hands. Because of the manual motor processor's limitations and people's attempts to cope with them, systematic interactions can occur between effects of various instructions about primary/secondary task priorities and the output mechanisms that they entail. Further simulations beyond the present ones show, for example, how successive responses may be produced either independently or in a grouped fashion, depending on whether or not they require the same manual motor processor and have a known a priori serial order (Meyer & Kieras, 1997b).

Prescriptions for Future PRP Studies

If the SRD model and EPIC architecture are taken seriously, then future PRP studies that strongly test the assumptions of our theoretical framework should be conducted. In order for such studies to be fully informative, they must adhere to certain prescriptions that follow from the present formal analyses.

Choice of task combinations. One prescription for future PRP studies concerns the particular task combinations that they include. As our RT equations and SOA constraints (Table 3) have indicated, some paths of processing that lead from Task 2 stimuli to Task 2 responses will not be taken if Task 1 RTs are relatively short compared with Task 2 RTs at long SOAs. When Task 1 is much easier than Task 2, response-selection processes for the two tasks may not temporally overlap, so only additive effects of SOA and response-selection difficulty may emerge, even though subjects are potentially able to select responses concurrently for the two tasks. In light of these considerations, future PRP studies should include task combinations such that Task 1 takes significantly longer to complete than does Task 2.

Numerosity of SOAs. A second prescription is that future PRP studies should include more SOAs than have been commonly used in the past. According to the SRD model and our parameterization of its prototype PRP curve (Figure 14), an adequate design would have at least five SOAs per experimental condition, so that each segment of the curve makes some contribution to observed Task 2 RTs. Studies with three or fewer SOAs, which populate the previous literature, are marginal at best for revealing the prototype's inherent shape and manifesting all of the possible information-processing paths that subjects might take to produce Task 2 responses.

Placement of SOAs. It is also essential that future PRP studies distribute their SOAs broadly along the time continuum. They should fully span the informative SOA range, so that both "very short" SOAs (i.e., ones that may enable post-selection slack during Task 2) and "very long" SOAs (i.e., ones that may enable advance Task 2 response preparation) are represented together with intermediate SOAs. Judging from the slopes of previously reported PRP curves, which sometimes exceed zero even at the longest included SOA, it appears that past PRP studies have not spanned the SOA range as much as one would like. Assuming Task 1 RTs are around 500 msec or more, a helpful rule of thumb might be that the longest SOAs in future studies should equal or exceed 1 sec.

Control of eye movements. In order for the preceding prescriptions to yield their full benefits, other aspects of subjects' performance must also be monitored and/or controlled better than has been done previously. To our knowledge, no PRP study has yet examined eye movements carefully during multiple-task performance. Instead, investigators have tended to ignore possible artifacts caused by eye movements, or they have tried to eliminate them through instructions about focusing on a visual fixation point, but the efficacy of these attempts has not been thoroughly checked. Such laxness is not desirable under conditions in which central response-selection bottlenecks are claimed. Instead, as our RT equations (Table 3) indicate, the latencies of intermediate eye movements must be evaluated rigorously to determine whether response-selection processes for primary and secondary tasks actually have an opportunity to overlap temporally.

Systematic manipulation of task instructions. Last, but not least, future PRP studies should systematically manipulate the instructions that subjects receive about task priorities and amounts of emphasis to be placed on individual tasks in dual-task situations (cf. Gopher, 1993). Research by Pashler (1990, 1994b) and others (e.g., Greenwald & Shulman, 1973; Koch, 1995; Lauber et al., 1994; Meyer et al., 1995; Ruthruff, Pashler, & Klaasen, 1995; Sanders, 1964) has shown that instructional manipulations can substantially change the obtained pattern of PRP effects. Given insights that the SRD model provides about these changes and their theoretical significance, such studies ought to continue and expand.

Relevance to Other Multiple-Task Situations

More generally, the EPIC architecture and SRD model may also contribute toward understanding multiple-task performance in other contexts beyond the PRP procedure. As mentioned earlier, Wickens (1980, 1984, 1991) has identified several ubiquitous phenomena -- difficulty insensitivity, structural-alteration effects, difficulty-structure uncoupling, and perfect time-sharing -- that occur during the performance of continuous dual tasks. Although simple bottleneck models and unitary resource theories cannot easily account for these phenomena, it is possible to do so through our framework.

For example, difficulty insensitivity (Isreal et al., 1980; Kantowitz & Knight, 1976; North, 1977; Wickens & Kessel, 1979) follows directly from EPIC's assumptions. According to them, this phenomenon can happen when no constraints are placed on the temporal order of primary-task and secondary-task responses, and the two tasks do not entail competitive access to shared perceptual or motor processors. If a primary task is made more difficult by increasing the number of cognitive production-rule steps required to complete it, then this will not necessarily increase the primary task's interference with a concurrent secondary task, because at a cognitive level, there may still be ample capacity for testing and applying the secondary task's production rules as well.

Similarly, structural-alteration effects (Brooks, 1968; Friedman et al., 1982; Harris et al., 1978; Martin, 1980; McFarland & Ashton, 1978; McLeod, 1977, 1978b; Treisman & Davies, 1973; Wickens, 1980; Wickens et al., 1983b; Wickens & Sandry, 1982) are readily interpretable in terms of our framework. Interference between primary and secondary tasks can be easily attenuated if they originally share the same perceptual and motor processors, but then one task is subsequently altered such that it relies on other perceptual or motor processors instead. Through the elimination of perceptual-motor competition, multiple tasks may benefit more fully from the capacity of EPIC's cognitive processor to execute several procedures concurrently.

EPIC likewise provides a natural treatment of difficulty-structure uncoupling. If the difficulty of the primary task is increased by making it entail more production-rule steps at a cognitive level, whereas primary-secondary task interference is decreased by having the two tasks rely on different perceptual-motor mechanisms, then the latter decrease can significantly outweigh the former increase. For example, as mentioned before, Wickens (1976) had subjects perform a secondary visual-manual tracking task together with either a primary manual force-generation or auditory signal-detection task. Although subjects reported that the signal-detection task was harder than the force-generation task, the detection task actually interfered less with the secondary tracking task. From EPIC's perspective, this lesser interference is attributable to the fact that the signal-detection task, unlike the force-generation task, did not require the manual motor processor on which the tracking task relied.

Even more striking are occasional observations of essentially perfect time-sharing that have been reported in the literature (Allport et al., 1972; Greenwald & Shulman, 1973; Hirst et al., 1980; Koch, 1995; Shaffer; 1975). The studies that have produced them share some special features: the perceptual and motor mechanisms used for one task (e.g., vocal shadowing of auditory messages) are entirely distinct from those used for another concurrent task (e.g., manual playing of piano music from a printed score); the tasks may be performed through independent sets of well-learned production rules; and the responses for one task can have any temporal order relative to those for the other task. These are indeed conditions that, according to EPIC and the SRD model, might enable unimpeded multiple-task performance.

For additional results that support the present theoretical framework, readers may consult our next forthcoming report (Meyer & Kieras, 1997b).

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Appendix 1

Production Rules from SRD Model for Auditory-Manual Task 1 with Two S-R Pairs

Below are representative production rules that the SRD model uses in performing an auditory-manual Task 1 under the standard PRP procedure. For simplicity, these rules have been edited somewhat, and certain ancillary "record keeping" rules have been omitted. We assume here that Task 1 involves two stimuli (800 and 1200 Hz tones) paired respectively with two responses (keypresses by the left-middle and left-index fingers). Among the rules for dealing with these S-R pairs are ones that start Task 1, select Task 1 responses in immediate response-transmission mode, implement a repetition by-pass feature during response selection, and declare Task 1 to be "done." For example, these rules can perform a version of Task 1 that was included as part of the PRP study by Hawkins et al. (1979).

Rule For Task 1 Initiation:

```
(Start Task 1
IF
((GOAL DO TASK 1)
 (AUDITORY TONE ?S ON)
 (NOT (TASK 1 UNDERWAY)))
THEN
((ADDDB (STEP DO CHECK FOR LOW TONE))
 (ADDDB (TASK 1 UNDERWAY))))
```

Rules For Task 1 Response Selection:

```
(Repetition By-pass For Task 1
IF
((GOAL DO TASK 1)
 (STEP DO CHECK FOR LOW TONE)
 (AUDITORY TONE ?S ON)
 (LAST TASK 1 STIMULUS IS ?S)
 (LAST TASK 1 RESPONSE IS ?R))
THEN
((SEND-TO-MOTOR MANUAL PERFORM ?R)
 (ADDDB (STEP WAIT-FOR TASK 1 RESPONSE COMPLETION))
 (ADDDB (TASK 1 RESPONSE UNDERWAY))
 (DELDB (AUDITORY TONE ?S ON))
 (ADDDB (LAST TASK 1 STIMULUS IS ?S))
 (ADDDB (LAST TASK 1 RESPONSE IS ?R))
 (DELDB (STEP DO CHECK FOR LOW TONE))))

(Repetition Cleanup For Task 1
IF
((GOAL DO TASK 1)
 (STEP DO CHECK FOR LOW TONE)
 (LAST TASK 1 STIMULUS IS ?S)
 (LAST TASK 1 RESPONSE IS ?R))
THEN
((DELDB (LAST TASK 1 STIMULUS IS ?S))
 (DELDB (LAST TASK 1 RESPONSE IS ?R))))
```

```
(Select And Transmit Left-Middle Response For Low Tone
IF
((GOAL DO TASK 1)
 (STEP DO CHECK FOR LOW TONE)
 (AUDITORY TONE 800 ON)
 (NOT (LAST TASK 1 STIMULUS IS 800)))
THEN
((SEND-TO-MOTOR MANUAL PERFORM LEFT-MIDDLE)
 (ADDDB (STEP WAIT-FOR TASK 1 RESPONSE COMPLETION))
 (ADDDB (TASK 1 RESPONSE UNDERWAY))
 (DELDB (STEP DO CHECK FOR LOW TONE))
 (DELDB (AUDITORY TONE 800 ON))
 (ADDDB (LAST TASK 1 STIMULUS IS 800))
 (ADDDB (LAST TASK 1 RESPONSE IS LEFT-MIDDLE))))

(Advance To Check For High Tone
IF
((GOAL DO TASK 1)
 (STEP DO CHECK FOR LOW TONE)
 (NOT (LAST TASK 1 STIMULUS IS 1200))
 (NOT (AUDITORY TONE 800 ON)))
THEN
((ADDDB (STEP DO CHECK FOR HIGH TONE))
 (DELDB (STEP DO CHECK FOR LOW TONE))))

(Select And Transmit Left-Index Response For High Tone
IF
((GOAL DO TASK 1)
 (STEP DO CHECK FOR HIGH TONE)
 (AUDITORY TONE 1200 ON))
THEN
((SEND-TO-MOTOR MANUAL PERFORM LEFT-INDEX)
 (ADDDB (STEP WAIT-FOR TASK 1 RESPONSE COMPLETION))
 (ADDDB (TASK 1 RESPONSE UNDERWAY))
 (DELDB (STEP DO CHECK FOR HIGH TONE))
 (DELDB (AUDITORY TONE 1200 ON))
 (ADDDB (LAST TASK 1 STIMULUS IS 1200))
 (ADDDB (LAST TASK 1 RESPONSE IS LEFT-INDEX))))
```

Rule For Task 1 Completion:

```
(Declare Task 1 Is "Done"
IF
((GOAL DO TASK 1)
 (STRATEGY UNLOCK ON MOTOR-SIGNAL MANUAL STARTED LEFT)
 (STEP WAIT-FOR TASK 1 RESPONSE COMPLETION)
 (MOTOR-SIGNAL MANUAL STARTED LEFT ?FINGER))
THEN
((DELDB (STEP WAIT-FOR TASK 1 RESPONSE COMPLETION))
 (DELDB (MOTOR-SIGNAL MANUAL STARTED LEFT ?FINGER))
 (DELDB (TASK 1 UNDERWAY))
 (DELDB (TASK 1 RESPONSE UNDERWAY))
 (DELDB (GOAL DO TASK 1))
 (ADDDB (TASK 1 DONE))))
```

Appendix 2

Production Rules from SRD Model for Visual-Manual Task 2 with Two S-R Pairs

Below are representative production rules that the SRD model uses in performing a visual-manual Task 2 under the standard PRP procedure. For simplicity, these rules have been edited somewhat, and certain ancillary "record keeping" rules have been omitted. We assume here that Task 2 involves two stimuli (the digits "2" and "3") paired respectively with two responses (keypresses by right-index and right-middle fingers). Among the rules for dealing with these S-R pairs are ones that start Task 2, select Task 2 responses in deferred or immediate response-transmission mode, release Task 2 responses that have been selected in deferred mode, implement a repetition by-pass feature during response selection, and complete terminal book-keeping after Task 2 is declared to be "done." For example, these rules would be appropriate to perform the "easy" version of Task 2 that was included as part of the PRP study by Hawkins et al. (1979).

Rules For Task 2 Initiation In Deferred Or Immediate Transmission Mode:

```
(Start Deferred Mode Task 2
IF
((GOAL DO TASK 2)
 (STRATEGY TASK 2 MODE IS DEFERRED)
 (VISUAL RIGHT DIGIT ?S ON)
 (NOT (LAST TASK 2 STIMULUS IS ?S))
 (NOT (TASK 2 UNDERWAY)))
THEN
((ADDDB (STEP DO CHECK FOR FIRST DIGIT))
 (ADDDB (TASK 2 UNDERWAY))

(Start Immediate Mode Task 2
IF
((GOAL DO TASK 2)
 (STRATEGY TASK 2 MODE IS IMMEDIATE)
 (VISUAL RIGHT DIGIT ?S ON)
 (NOT (LAST TASK 2 STIMULUS IS ?S))
 (NOT (TASK 2 UNDERWAY)))
THEN
((ADDDB (STEP DO CHECK FOR FIRST DIGIT))
 (ADDDB (TASK 2 UNDERWAY))
```

Rules For Task 2 Response Selection And Transmission In Deferred Mode:

```
(Repetition By-Pass For Deferred Mode Task 2
IF
((GOAL DO TASK 2)
 (STRATEGY TASK 2 MODE IS DEFERRED)
 (VISUAL RIGHT DIGIT ?S ON)
 (LAST TASK 2 STIMULUS IS ?S)
 (LAST TASK 2 RESPONSE IS ?R)
 (NOT (TASK 2 UNDERWAY)))
THEN
((ADDDB (RESPONSE IS ?R))
 (ADDDB (STEP WAIT-FOR TASK 2 RESPONSE PERMISSION))
 (ADDDB (TASK 2 UNDERWAY))
 (DELDB (VISUAL RIGHT DIGIT ?S ON))
 (ADDDB (LAST TASK 2 STIMULUS IS ?S))
 (ADDDB (LAST TASK 2 RESPONSE IS ?R))))
```

```
(Repetition Cleanup For Deferred Mode Task 2
IF
((GOAL DO TASK 2)
 (STRATEGY TASK 2 MODE IS DEFERRED)
 (LAST TASK 2 STIMULUS IS ?S)
 (LAST TASK 2 RESPONSE IS ?R)
 (VISUAL RIGHT DIGIT ??? ON)
 (NOT (TASK 2 UNDERWAY)))
THEN
((DELDB (LAST TASK 2 STIMULUS IS ?S))
 (DELDB (LAST TASK 2 RESPONSE IS ?R))))

(Select And Store Deferred Right-Index Response For Digit 2
IF
((GOAL DO TASK 2)
 (STRATEGY TASK 2 MODE IS DEFERRED)
 (STEP DO CHECK FOR FIRST DIGIT)
 (VISUAL RIGHT DIGIT 2 ON))
THEN
((ADDDB (RESPONSE IS RIGHT-INDEX))
 (ADDDB (STEP WAIT-FOR TASK 2 RESPONSE PERMISSION))
 (DELDB (STEP DO CHECK FOR FIRST DIGIT))
 (DELDB (VISUAL RIGHT DIGIT 2 ON))
 (ADDDB (LAST TASK 2 STIMULUS IS 2))
 (ADDDB (LAST TASK 2 RESPONSE IS RIGHT-INDEX))))

(Advance To Check For Digit 3 In Deferred Mode
IF
((GOAL DO TASK 2)
 (STRATEGY TASK 2 MODE IS DEFERRED)
 (STEP DO CHECK FOR FIRST DIGIT)
 (NOT (VISUAL RIGHT DIGIT 2 ON)))
THEN
((ADDDB (STEP DO CHECK FOR SECOND DIGIT))
 (DELDB (STEP DO CHECK FOR FIRST DIGIT))))

(Select And Store Deferred Right-Index Response For Digit 3
IF
((GOAL DO TASK 2)
 (STRATEGY TASK 2 MODE IS DEFERRED)
 (STEP DO CHECK FOR SECOND DIGIT)
 (VISUAL RIGHT DIGIT 3 ON))
THEN
((ADDDB (RESPONSE IS RIGHT-MIDDLE))
 (DELDB (STEP DO CHECK FOR SECOND DIGIT))
 (ADDDB (STEP WAIT-FOR TASK 2 RESPONSE PERMISSION))
 (DELDB (VISUAL RIGHT DIGIT 3 ON))
 (ADDDB (LAST TASK 2 STIMULUS IS 3))
 (ADDDB (LAST TASK 2 RESPONSE IS RIGHT-MIDDLE))))
```

```
(Release Deferred Task 2 Response When Permitted
IF
((GOAL DO TASK 2)
 (STRATEGY TASK 2 MODE IS DEFERRED)
 (STEP WAIT-FOR TASK 2 RESPONSE PERMISSION)
 (PERMIT TASK 2 RESPONSE)
 (RESPONSE IS ?RESPONSE))
THEN
((SEND-TO-MOTOR MANUAL PERFORM ?RESPONSE)
 (DELDB (STEP WAIT-FOR TASK 2 RESPONSE PERMISSION))
 (ADDDB (STEP WAIT-FOR TASK 2 RESPONSE COMPLETION))
 (DELDB (RESPONSE IS ?RESPONSE))
 (DELDB (PERMIT TASK 2 RESPONSE))))
```

Rules For Task 2 Response Selection And Transmission In Immediate Mode:

```
(Repetition By-Pass For Immediate Mode Task 2
IF
((GOAL DO TASK 2)
 (STRATEGY TASK 2 MODE IS IMMEDIATE)
 (VISUAL RIGHT DIGIT ?S ON)
 (LAST TASK 2 STIMULUS IS ?S)
 (LAST TASK 2 RESPONSE IS ?R)
 (NOT (TASK 2 UNDERWAY)))
THEN
((SEND-TO-MOTOR MANUAL PERFORM ?R)
 (ADDDB (STEP WAIT-FOR TASK 2 RESPONSE COMPLETION))
 (ADDDB (TASK 2 UNDERWAY))
 (DELDB (VISUAL RIGHT DIGIT ?S ON))
 (ADDDB (LAST TASK 2 STIMULUS IS ?S))
 (ADDDB (LAST TASK 2 RESPONSE IS ?R))))

(Repetition Cleanup For Immediate Mode Task 2
IF
((GOAL DO TASK 2)
 (STRATEGY TASK 2 MODE IS IMMEDIATE)
 (LAST TASK 2 STIMULUS IS ?S)
 (LAST TASK 2 RESPONSE IS ?R)
 (VISUAL RIGHT DIGIT ??? ON)
 (NOT (TASK 2 UNDERWAY)))
THEN
((DELDB (LAST TASK 2 STIMULUS IS ?S))
 (DELDB (LAST TASK 2 RESPONSE IS ?R))))

(Select And Transmit Immediate Right-Index Response For Digit 2
IF
((GOAL DO TASK 2)
 (STRATEGY TASK 2 MODE IS IMMEDIATE)
 (STEP DO CHECK FOR FIRST DIGIT)
 (VISUAL RIGHT DIGIT 2 ON))
THEN
((SEND-TO-MOTOR MANUAL PERFORM RIGHT-INDEX)
 (ADDDB (STEP WAIT-FOR TASK 2 RESPONSE COMPLETION))
 (DELDB (STEP DO CHECK FOR FIRST DIGIT))
 (DELDB (VISUAL RIGHT DIGIT 2 ON))
 (ADDDB (LAST TASK 2 STIMULUS IS 2))
 (ADDDB (LAST TASK 2 RESPONSE IS RIGHT-INDEX))))
```

```
(Advance To Check For Digit 3 In Immediate Mode
IF
((GOAL DO TASK 2)
 (STRATEGY TASK 2 MODE IS IMMEDIATE)
 (STEP DO CHECK FOR FIRST DIGIT)
 (NOT (VISUAL RIGHT DIGIT 2 ON)))
THEN
((DELDB (STEP DO CHECK FOR FIRST DIGIT))
 (ADDDB (STEP DO CHECK FOR SECOND DIGIT))))

(Select And Transmit Immediate Right-Index Response For Digit 3
IF
((GOAL DO TASK 2)
 (STRATEGY TASK 2 MODE IS IMMEDIATE)
 (STEP DO CHECK FOR SECOND DIGIT)
 (VISUAL RIGHT DIGIT 3 ON))
THEN
((SEND-TO-MOTOR MANUAL PERFORM RIGHT-MIDDLE)
 (DELDB (STEP DO CHECK FOR SECOND DIGIT))
 (ADDDB (STEP WAIT-FOR TASK 2 RESPONSE COMPLETION))
 (DELDB (VISUAL RIGHT DIGIT 3 ON))
 (ADDDB (LAST TASK 2 STIMULUS IS 3))
 (ADDDB (LAST TASK 2 RESPONSE IS RIGHT-MIDDLE))))
```

Rule For Task 2 Completion:

```
(Declare Task 2 Is "Done"
IF
((GOAL DO TASK 2)
 (STEP WAIT-FOR TASK 2 RESPONSE COMPLETION)
 (MOTOR-SIGNAL MANUAL STARTED RIGHT ?FINGER))
THEN
((DELDB (STEP WAIT-FOR TASK 2 RESPONSE COMPLETION))
 (DELDB (MOTOR-SIGNAL MANUAL STARTED RIGHT ?FINGER))
 (DELDB (GOAL DO TASK 2))
 (ADDDB (TASK 2 DONE))))
```

Appendix 3

Production Rules for Executive Process of The SRD Model

Below are production rules that the executive process of the SRD model uses with an auditory-manual Task 1 and visual-manual Task 2 under the standard PRP procedure. For simplicity, these rules have been edited somewhat, and certain ancillary "record keeping" rules have been omitted. We assume here that the contents of working memory have been preset already so the rules for initiating each dual-task PRP trial can be applied without further ado. For example, these rules are appropriate for simulating results from the PRP study by Hawkins et al. (1979).

Rules for Initiating Dual-Task PRP Trial:

```
(Initialize Contents Of Working Memory
IF
((GOAL DO DUAL-CRT TASK)
 (STRATEGY AUDITORY-MANUAL TASK 1)
 (STRATEGY VISUAL-MANUAL TASK 2)
 (VISUAL CENTER EVENT DETECTED ON)
 (NOT (TRIAL UNDERWAY)))
THEN
((SEND-TO-MOTOR MANUAL RESET)
 (ADDDB (TRIAL UNDERWAY))
 (ADDDB (GOAL DO TASK 1))
 (ADDDB (GOAL DO TASK 2))
 (ADDDB (STRATEGY TASK 2 MODE IS DEFERRED))
 (ADDDB (STRATEGY UNLOCK ON MOTOR-SIGNAL MANUAL STARTED LEFT))
 (DELDB (VISUAL CENTER EVENT DETECTED ON))
 (ADDDB (STEP MOVE EYES TO RIGHT))
 (ADDDB (STEP WAIT-FOR TASK 1 DONE))))

(Move Eyes To Look At Task 2 Stimulus Location
IF
((GOAL DO DUAL-CRT TASK))
 (STRATEGY AUDITORY-MANUAL TASK 1)
 (STRATEGY VISUAL-MANUAL TASK 2)
 (STEP MOVE EYES TO RIGHT)
THEN
((SEND-TO-MOTOR OCULAR PERFORM RIGHT-SMALL)))
```

Rules For Unlocking Task 2:

```
(Permit Transmission Of Pre-Selected And Deferred Task 2 Response
IF
((GOAL DO DUAL-CRT TASK)
 (STRATEGY AUDITORY-MANUAL TASK 1)
 (STRATEGY VISUAL-MANUAL TASK 2)
 (STEP WAIT-FOR TASK 1 DONE)
 (TASK 1 DONE)
 (TASK 2 UNDERWAY)
 (RESPONSE IS ???))
THEN
((SEND-TO-MOTOR MANUAL RESET)
 (DELDB (STEP WAIT-FOR TASK 1 DONE))
 (DELDB (TASK 1 DONE))
 (ADDDB (PERMIT TASK 2 RESPONSE))
 (ADDDB (STEP WAIT-FOR TASK 2 DONE))))
```

```
(Suspend Task 2 When No Pre-Selected Response Is In Working Memory
IF
((GOAL DO DUAL-CRT TASK)
 (STRATEGY AUDITORY-MANUAL TASK 1)
 (STRATEGY VISUAL-MANUAL TASK 2)
 (STEP WAIT-FOR TASK 1 DONE)
 (TASK 1 DONE)
 (NOT (RESPONSE IS ???)))
THEN
((DELDB (GOAL DO TASK 2))
 (DELDB (STEP WAIT-FOR TASK 1 DONE))
 (DELDB (TASK 1 DONE))
 (ADDDB (STEP CHECK TASK 2 STATE))))

(Update Working Memory After Task 1 Is "Done"
IF
((GOAL DO DUAL-CRT TASK)
 (STRATEGY AUDITORY-MANUAL TASK 1)
 (STRATEGY VISUAL-MANUAL TASK 2)
 (STEP WAIT-FOR TASK 1 DONE)
 (TASK 1 DONE))
THEN
((DELDB (TASK 1 DONE))))

(Permit Transmission Of Response Selected When Suspension Occurs
IF
((GOAL DO DUAL-CRT TASK)
 (STRATEGY AUDITORY-MANUAL TASK 1)
 (STRATEGY VISUAL-MANUAL TASK 2)
 (STEP CHECK TASK 2 STATE)
 (RESPONSE IS ???))
THEN
((SEND-TO-MOTOR MANUAL RESET)
 (ADDDB (GOAL DO TASK 2))
 (DELDB (STEP CHECK TASK 2 STATE))
 (ADDDB (PERMIT TASK 2 RESPONSE))
 (ADDDB (STEP WAIT-FOR TASK 2 DONE))))

(Shift Response Transmission For Task 2 To Immediate Mode
IF
((GOAL DO DUAL-CRT TASK)
 (STRATEGY AUDITORY-MANUAL TASK 1)
 (STRATEGY VISUAL-MANUAL TASK 2)
 (STEP CHECK TASK 2 STATE)
 (NOT (RESPONSE IS ???)))
THEN
((ADDDB (GOAL DO TASK 2))
 (DELDB (STRATEGY TASK 2 MODE IS DEFERRED))
 (ADDDB (STRATEGY TASK 2 MODE IS IMMEDIATE))))
```

```
(Initiate Optional Suspension Waiting Time
IF
((GOAL DO DUAL-CRT TASK)
 (STRATEGY AUDITORY-MANUAL TASK 1)
 (STRATEGY VISUAL-MANUAL TASK 2)
 (STEP CHECK TASK 2 STATE)
 (NOT (RESPONSE IS ???)))
THEN
((DELDB (STEP CHECK TASK 2 STATE))
 (ADDDB (STEP WAIT-FOR SUSPENSION END))
 (ADDDB (SUSPENSION WAIT 1))))

(Resume Response Selection For Task 2 When Wait Is Done
IF
((GOAL DO DUAL-CRT TASK)
 (STRATEGY AUDITORY-MANUAL TASK 1)
 (STRATEGY VISUAL-MANUAL TASK 2)
 (STEP WAIT-FOR SUSPENSION END)
 (SUSPENSION WAIT ENDED))
THEN
((DELDB (SUSPENSION WAIT ENDED))
 (ADDDB (GOAL DO TASK 2))
 (DELDB (STEP WAIT-FOR SUSPENSION END))
 (ADDDB (STEP WAIT-FOR TASK 2 DONE))))
```

Rule For Ancipatory Task 2 Movement-Feature Preparation:

```
(Prepare Right-Hand Task 2 Response
IF
((GOAL DO DUAL-CRT TASK)
 (STRATEGY AUDITORY-MANUAL TASK 1)
 (STRATEGY VISUAL-MANUAL TASK 2)
 (GOAL DO TASK 2)
 (TACTILE MANUAL FINISHED LEFT ?FINGER)
 (NOT (TASK 2 UNDERWAY))
 (NOT (VISUAL RIGHT DIGIT ??? ON))
THEN
((SEND-TO-MOTOR MANUAL PREPARE RIGHT)
 (DELDB (TACTILE MANUAL FINISHED LEFT ?FINGER))))
```

Rules For Completing Dual-Task PRP Trial:

```
(Update Contents Of Working Memory At End Of Trial
IF
((GOAL DO DUAL-CRT TASK)
 (STRATEGY AUDITORY-MANUAL TASK 1)
 (STRATEGY VISUAL-MANUAL TASK 2)
 (STEP WAIT-FOR TASK 2 DONE)
 (TASK 2 DONE))
THEN
((DELDB (S2 IS ON))
 (DELDB (GOAL DO TASK 2))
 (DELDB (STEP WAIT-FOR TASK 2 DONE))
 (DELDB (TASK 1 DONE))
 (DELDB (TASK 2 DONE))
 (DELDB (STRATEGY TASK 2 MODE IS DEFERRED))
 (DELDB (STRATEGY TASK 2 MODE IS IMMEDIATE))
 (DELDB (STRATEGY UNLOCK ON MOTOR-SIGNAL MANUAL STARTED LEFT))
 (DELDB (TRIAL UNDERWAY))))

(Reposition Eyes On Central Fixation Point
IF
((GOAL DO DUAL-CRT TASK)
 (STRATEGY AUDITORY-MANUAL TASK 1)
 (STRATEGY VISUAL-MANUAL TASK 2)
 (STEP WAIT-FOR TASK 2 DONE)
 (TASK 2 DONE))
THEN
((SEND-TO-MOTOR OCULAR PERFORM CENTER)))
```

Appendix 4

Parameter Estimation

On the basis of Equations 1 through 17 in the preceding text (see Table 3), it is possible to estimate appropriate numerical values for some of the SRD model's parameters. These estimates maximize the goodness-of-fit between simulated and empirical mean RTs. We achieve this objective by inserting empirical mean RTs into the left sides of the previous theoretical equations and then rearranging terms to determine what parameter values are solutions to them.

Such estimation is not possible in every case, however. This limitation arises because the SRD model yields fewer linearly independent RT equations than are required to estimate all of its parameters separately. We therefore begin by initially setting the mean values of some parameters on an a priori basis. Then, following these initial assignments, we apply our theoretical equations to estimate the means of other parameters.

The next subsections describe how some parameters of the Task 1 processes, Task 2 processes, and executive processes are estimated in this way.

Estimation of Task 1 Process Parameters

Before each simulation, the mean values of three distinct temporal parameters must be assigned for Task 1 processes. They include the Task 1 stimulus-identification time, Task 1 response-selection time, and Task 1 response-transduction time. As mentioned in the text, the mean of the response-selection time is set indirectly through the production rules that we specify to select Task 1 responses. Also, under some conditions, we guesstimate the mean of the response-transduction time. After these preliminaries, the means of other Task 1 parameters are estimated with Equation 1.

Stimulus-identification time. For example, the Task 1 stimulus-identification time (t_{i1}) may be estimated by rearranging Equation 1 to have the following form:

$$t_{i1} = RT_1 - t_g - t_{s1} - t_{m1} - t_{r1}, \qquad (A4.1)$$

where RT_1 denotes the theoretical Task 1 RT, t_g denotes the working-memory gating time, t_{s1} denotes the Task 1 response-selection time, t_{m1} denotes the Task 1 movement-production time, and t_{r1} denotes the Task 1 response-transduction time. By inserting an empirical mean Task 1 RT along with other pre-assigned parameter values on the right side of Equation A4.1, we estimate the appropriate mean of t_{i1} on the left side.[33] The obtained estimate is used in EPIC's perceptual processor that services the Task 1 stimulus modality during our simulation runs.

Our simulations of results from the PRP study by Hawkins et al. (1979) illustrate these preceding steps. Before simulating their auditory-manual Task 1 RTs, we made a priori production-rule specifications, parameter assignments, and guesstimations such that the means of t_g, t_{s1}, t_{m1}, and t_{r1} were set respectively to 25, 110, 150, and 10 ms. Then we inserted them in the right side of Equation A4.1 and replaced RT_1 with a value of 630 ms, the approximate empirical mean RT for the auditory-manual Task 1, averaged across SOAs and Task 2 difficulty levels. This yielded 335 ms as an estimate of the mean time to identify auditory tones.

Response-transduction time. Through a similar approach, Equation 1 may also be rearranged to obtain an expression for the Task 1 response-transduction time:

---

33 As mentioned before (Table 2), some parameters on the right side of Equation A4.1 are assigned mean values that stay the same throughout our simulations and do not depend on the empirical Task 1 or Task 2 RTs. Specifically, the mean of the working-memory gating time (t_g) always equals 25 ms, half the mean of the cognitive-processor cycle duration (t_c). Also, because the Task 1 movement-production time is defined as $t_{m1} = (n_f \times t_f) + t_a$, its mean stems from initial fixed settings made to the number of movement features ($n_f = 2$), mean time per feature ($t_f = 50$), and mean action-initiation time ($t_a = 50$), which are used by EPIC's motor processors in producing overt responses.

$$t_{r1} = \mathrm{RT}_1 - t_g - t_{i1} - t_{s1} - t_{m1} \,. \tag{A4.2}$$

Substituting prerequisite values on the right side of Equation A4.2 yields an estimate of the mean that t_{r1} should have on the left side. This estimate is used by our environment-simulation program to transduce responses in Task 1's motor modality.

For example, along with their auditory-manual Task 1, Hawkins et al. (1979) also included an auditory-vocal Task 1 in which the stimuli were tones and the responses were spoken words. There the empirical mean Task 1 RT equaled about 740 ms. Thus, we can insert it on the right side of Equation A4.2, along with our prior estimate of the mean auditory-tone identification time (i.e., t_{i1} = 335 ms) and other prerequisite values, obtaining an estimated 120 ms for the mean time required to transduce vocal responses. Interestingly, the latter estimate is about 110 ms greater than the previous one that we guesstimated for manual keypress responses (cf. Table 4), consistent with the lengthy delays that can occur between the start of articulatory movements and the onset of speech sounds (Ladefoged, 1975).

Estimation of Task 2 Process Parameters

Mean values of parameters for Task 2 processes of the SRD model may be assigned in much the same way as for Task 1 processes. In some cases, such as the Task 2 response-selection time (t_{s2}), feature-preparation benefit (t_{p2}), and response-transduction time (t_{r2}), we set their means by production-rule programming and a priori guesstimation. Then, following these initial assignments, the means of other parameters are estimated to maximize the goodness-of-fit between simulated and empirical mean Task 2 RTs.

Stimulus-identification and response-transduction times. For example, before some simulations, we rearrange Equation 16 to express the Task 2 stimulus-identification time in terms of a difference between Task 2 RTs and other related parameters. This yields

$$t_{i2} = \mathrm{RT}_2(\mathrm{SOA}_5 \mid \text{Path 5}) - \max(0, t_{o2} - \mathrm{SOA}_5) - t_g - t_{s2} - t_{m2} - t_{r2} + t_{p2} \,, \tag{A4.3}$$

where SOA_5 is a very long SOA that presumably leads to Path 5 of processing for Task 2. An appropriate mean for t_{i2} is then estimated by substituting an empirical mean Task 2 RT (i.e., the observed manifestation of $\mathrm{RT}_2(\mathrm{SOA}_5 \mid \text{Path 5})$) along with other prerequisite values on the right side of Equation A4.3. Specifically, with respect to Hawkins et al.'s (1979) PRP study, which involved a visual-manual Task 2, the estimated mean Task 2 visual stimulus-identification time turned out to be 245 ms, which is 90 ms less than the corresponding auditory stimulus-identification time (Table 4).[34]

Furthermore, with the mean of t_{i2} in hand, it is sometimes possible to estimate additional parameter values. Whenever an empirical PRP study includes orthogonal combinations of stimulus (e.g., auditory or visual) and response (e.g., vocal or manual) modalities as part of Task 2, our rearrangements of Equation 16 yield estimates for the means of not only Task 2 stimulus-identification times but also Task 2 response-transduction times (t_{r2}). For example, in simulating results from various Task 2 conditions of Pashler's (1990, Exps. 1 and 2) PRP study, we (Meyer & Kieras, 1997) have determined that stimulus-identification times there were a bit longer for auditory tones than visual letters (mean t_{i2} = 285 vs. 260 ms), and response-transduction times were longer for vocal words than manual keypresses (mean t_{r2} = 50 vs. 40 ms). This latter pattern is consistent with what emerged from our parameter estimation for Hawkins et al. (1979).

Response-selection times. Interestingly, it might also be possible to estimate appropriate means for Task 2 response-selection times (t_{s2}), because only certain values of them can satisfy particular linear combinations of Equations 4, 7, 10, and 13. Combining these equations and rearranging terms, we have

[34] Given that the auditory stimuli of Hawkins et al. (1979) required relatively unfamiliar tone discriminations, whereas their visual stimuli required familiar letter discriminations, the present difference between estimated auditory and visual stimulus-identification times seems at least somewhat plausible.

$$t_{s2} = \mathrm{RT}_2(\mathrm{SOA}_3 \mid \text{Path } 3) + \mathrm{RT}_2(\mathrm{SOA}_4 \mid \text{Path } 4)$$
$$- \mathrm{RT}_2(\mathrm{SOA}_1 \mid \text{Path } 1) - \mathrm{RT}_2(\mathrm{SOA}_2 \mid \text{Path } 2) + t_v + \mathrm{SOA}_3 - \mathrm{SOA}_1 , \qquad \text{(A4.4)}$$

where SOA_1 is a very short SOA defined by Inequality 2, SOA_2 is a moderately short SOA defined by Inequality 5, SOA_3 is an intermediate SOA defined by Inequality 8, SOA_4 is a moderately long SOA defined by Inequality 11, and t_v is the minimum unlocking duration of the SRD model's executive process. Our simulations assume that the minimum unlocking duration has the same mean across all conditions (i.e., $t_v = 100$ ms).[35] Thus, whenever a study happens to include four SOAs that always satisfy Inequalities 2, 5, 8, and 11, respectively, then we may substitute them along with the pre-set mean of t_v and the corresponding empirical mean Task 2 RTs in the right side of Equation A4.4, obtaining an estimated mean for t_{s2}.[36]

Estimation of Executive-Process Parameters

Supplementing our estimation of the parameters used in Task 1 and Task 2 processes, we may estimate means of some parameters for the SRD model's executive process. Of particular interest here are two executive-process parameters. First there is the unlocking-onset latency (t_u), which intervenes between the moments when the Task 1 response is selected and the executive process starts the steps for shifting Task 2 from the deferred to the immediate response-transmission mode. Second there is the suspension waiting time (t_w), which contributes to the total time that response-selection for Task 2 remains inactivated during the unlocking phase.

Unlocking-onset latency. Combining Equation 4 with Equation 16 and rearranging terms gives us an expression for the unlocking-onset latency,

$$t_u = \mathrm{RT}_2(\mathrm{SOA}_1 \mid \text{Path } 1) - \mathrm{RT}_2(\mathrm{SOA}_5 \mid \text{Path } 5) + t_{i2} + t_{s2} - t_{p2} - t_{i1} - t_{s1} - t_v + \mathrm{SOA}_1 , \qquad \text{(A4.5)}$$

where SOA_1 and SOA_5 are very short and very long SOAs that, respectively, lead to Paths 1 and 5 of processing for Task 2. We estimate the unlocking-onset latency, t_u, by inserting empirical mean RTs (i.e., observed manifestations of $\mathrm{RT}_2(\mathrm{SOA}_1 \mid \text{Path } 1)$ and $\mathrm{RT}_2(\mathrm{SOA}_5 \mid \text{Path } 5)$) along with other a priori values on the right side of Equation A4.5.

Interestingly, the mean unlocking-onset latencies that are estimated through Equation A4.5 have a consistent interpretable pattern across typical empirical PRP studies. Under conditions in which subjects have received relatively little practice (e.g., on the order of a thousand trials or less), t_u has rather long values. For example, in our simulations of results from the PRP study by Hawkins et al. (1979) with an auditory-manual Task 1 and visual-manual Task 2, the unlocking-onset latency is typically greater than 200 ms (Table 4), which implies that the executive process begins unlocking Task 2 at about the same time as the overt Task 1 responses start. However, under conditions in which test subjects receive extensive practice (e.g., several thousand trials or more), t_u is much shorter. For example, our simulations of results from the PRP study by Karlin and Kestenbaum (1968) have set the mean unlocking-onset latency to be only about 100 ms (Meyer & Kieras, 1997); this implies that the executive process begins unlocking Task 2 soon after the cognitive processor selects the Task 1 response. Apparently, extensive practice may induce subjects to schedule the processes for Tasks 1 and 2 with more temporal overlap between them (cf. Lauber, Schumacher, Glass, Zurbriggen, Kieras, & Meyer, 1994; Meyer, Kieras, Lauber, Schumacher, Glass, Zurbriggen, Gmeindl, & Apfelblat, 1995).

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[35] It is also assumed here that the ocular-orientation time for Task 2 has a relatively small value (e.g., $t_{o2} = 0$).

[36] Of course, this estimation is only possible for studies that include at least four different SOAs. Furthermore, the empirical Task 2 RTs must be relatively stable, and the SOAs must be placed so that they actually range from "very short" to "moderately long." Because most extant studies do not satisfy these prerequisites, this latter limitation often precludes the application of Equation A4.4.

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