The Dynamics of Cognition and Action: 
Mental Processes Inferred From Speed–Accuracy Decomposition

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Measurements of reaction time have played a major role in developing theories about the mental processes that underlie sensation, perception, memory, cognition, and action. The interpretation of reaction time data requires strong assumptions about how subjects trade accuracy for speed of performance and about whether there is a discrete or continuous transmission of information from one component process to the next. Conventional reaction time and speed–accuracy trade-off procedures are not, by themselves, sufficiently powerful to test these assumptions. However, the deficiency can be remedied in part through a new speed–accuracy decomposition technique. To apply the technique, one uses a hybrid mixture of (a) conventional reaction time trials in which subjects must process a given test stimulus with high accuracy and (b) peremptory response-signal trials in which subjects must make prompted guesses before stimulus processing has been finished. Data from this "titrated reaction time procedure" are then analyzed in terms of a parallel sophisticated-guessing model, under which normal mental processes and guessing processes are assumed to race against each other in producing overt responses. With the model, one may estimate the amount of partial information that subjects have accumulated about a test stimulus at each intermediate moment during a reaction time trial. Such estimates provide deeper insights into the rate at which partial information is accumulated over time and into discrete versus continuous modes of information processing. An application of speed–accuracy decomposition to studies of word recognition illustrates the potential power of the technique.

People do not think or act instantaneously. The time required to take action depends systematically on mental and physical processes that precede an overt response. Thus, throughout many areas of psychology, conclusions about the nature of mind and body have been based on measurements of human reaction time.\(^1\) Past uses of reaction time data extend from studies of elementary sensory mechanisms (e.g., Green & Luce, 1973) to studies of perception (e.g., Garner, 1962, 1970), attention and automaticity (e.g., Keele, 1973; Schneider & Shiffrin, 1977), knowledge structure (e.g., J. R. Anderson, 1976; Collins & Quillian, 1969), semantic priming (e.g., Meyer & Schvaneveldt, 1971, 1976; Neely, 1976), memory retrieval (e.g., Meyer, 1970; S. Sternberg, 1969, 1975), sentence comprehension (e.g., Clark & Chase, 1972; Meyer, 1973, 1975; G. A. Miller, 1962), reasoning (e.g., R. J. Sternberg, 1977), problem solving (e.g., J. C. Thomas & Greeno, 1974), and movement control (e.g., Rosenbaum, 1980; S. Sternberg, Monsell, Knoll, & Wright, 1978). Such research is relevant, in turn, to numerous other topics, including social, developmental, personality, and clinical psychology (e.g., K. J. Anderson & Revelle, 1982; Dickman & Meyer, 1988; Eysenck, 1974; Holyoak & Gordon, 1983). Because of the heavy emphasis placed on reaction time data, it is especially important for them to have a solid conceptual substrate.

This article is intended to strengthen the theoretical and empirical foundations on which reaction times are measured and interpreted. In what follows, we first survey various models of human information processing that have been developed on the basis of reaction time data and other related measures (e.g., speed–accuracy trade-off curves). Next we outline several limitations of the empirical approaches by which such models have been tested. Then we introduce a hybrid procedure and analytical framework that may help to overcome some of these limitations. An application of this framework, which involves a new speed–accuracy decomposition technique, will be reported to

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\(^1\) In representative issues of the Journal of Experimental Psychology: Human Perception and Performance, up to 40% of the articles have used measures of reaction time to reach their conclusions. Substantial percentages of articles involving reaction time measures may also be found in other related publications (e.g., Cognitive Psychology: Memory & Cognition, and Perception & Psychophysics).
demonstrate its power for analyzing the intermediate products of rapid mental processes.

Models of Information Processing

Research with conventional reaction time procedures has yielded numerous alternative models of human information processing. For purposes of exposition, a convenient way to classify these models is in terms of the assumptions that they make about temporal relations among component mental processes (Luce, 1986; E. E. Smith, 1968; Townsend & Ashby, 1983). According to some models, the processes used to perform a cognitive task occur in a strict serial fashion, with only one process operating at a given time. Such serial processing may have a completely predetermined order, in which each component always receives an input from the same source (i.e., its immediate predecessor) and always sends an output to the same recipient (i.e., its immediate successor). According to other models, processing is not strictly serial. Instead, these models assume that multiple processes operate simultaneously (i.e., in parallel). In this case, it is possible, although not necessary, for outputs to pass back and forth among processes without any set order of precedence. Because of its fundamental status, the serial-versus-parallel distinction bears directly on the theoretical interpretation of reaction times (Pachella, 1974) and has provided a focus of considerable debate in the reaction-time literature (Townsend & Ashby, 1983).

A second basic distinction concerns the nature of the information accumulated and transmitted by component mental processes. Some models assume that as a process proceeds from start to finish, it progresses through a finite number of discrete internal states, which represent increasing degrees of specificity about what its output(s) should be. Upon reaching the last of these states, the process may produce an output consisting of a single quantal packet of information, or it may produce several intermediate packets along the way, with some period of time separating the transmission of one packet from the transmission of the next. Alternatively, other models assume that a process progresses through a continuous range of internal states, corresponding to a gradual accumulation of information or activation over time. In this case, the output may consist of a continuous information flow, or a single discrete output may occur when some selected threshold state is reached. Like the serial-versus-parallel distinction, the discrete-versus-continuous distinction bears directly on the theoretical interpretation of reaction times (Meyer, Yantis, Osman, & Smith, 1984, 1985; J. Miller, 1982a, 1983), and it, too, has provided a focus of considerable debate in the reaction time literature.

These two theoretical distinctions may be combined to create a variety of competing models. It is possible, for example, to imagine parallel-process models in which the components produce either discrete outputs (e.g., J. Miller, 1982a, 1983) or a continuous flow of information (e.g., McClelland, 1979). Similarly, each of several serial processes might produce either discrete outputs (e.g., S. Sternberg, 1969) or a continuous information flow (e.g., Ratcliff, 1978), even though that information is not used by its recipient until after its source has finished operating. There are also models involving hybrid combinations of serial and parallel processing together with discrete or continuous outputs (Schweikert, 1978, 1983). Nevertheless, it is perhaps most plausible and parsimonious to associate discrete outputs with serial processes and continuous outputs with parallel processes, as many theorists have done (e.g., Donders, 1868/1969; Eriksen & Schultz, 1979; McClelland, 1979; Meyer, Schvaneveldt, & Ruddy, 1974, 1975; Rosenbaum, 1980; S. Sternberg, 1969; Turvey, 1973; Yellott, 1971).

To illustrate such alternative classes of models concretely, we will consider three influential cases: the discrete stage model of S. Sternberg (1969), the cascade model of McClelland (1979), and the stochastic diffusion model of Ratcliff (1978, 1988; for further discussion of these models, see Meyer et al., 1984; Meyer, Yantis, Osman, & Smith, 1985).

Discrete Stage Model

A prototypical example of serial processes with quantal all-or-none outputs is embodied in the discrete stage model of S. Sternberg (1969). Under this model, whose heritage dates back to the work of Donders (1868/1969), the performance of various cognitive tasks entails a sequence of temporally separate processing stages that include stimulus encoding, memory retrieval, decision, and response preparation (see Figure 1). At the end of each stage, a single discrete packet of information is passed to its immediate successor, and no stage has access to the partial products of its predecessors while they are still active.

S. Sternberg (1969, 1975) applied the discrete stage model to account for reaction time data obtained from experiments on short-term recognition memory. Such experiments have revealed that when subjects memorize a brief list of items (e.g., one to six letters) and then decide whether a presented test item occurred on the list, their mean reaction time increases linearly with list length at a rate of about 40 ms per item. The effect of list length does not interact with certain other factors (e.g., the legibility of the test items), which affect mean reaction times additively. In S. Sternberg's (1969) account, the list-length effect was attributed to a serial exhaustive search of the memorized list that yields either a match or mismatch with the presented test item. The additive effects of other factors were attributed to systematic changes in the durations of complementary processing stages (e.g., stimulus encoding).

As this example demonstrates, the discrete stage model has a number of attractive features. It is both simple and elegant, providing a useful theoretical framework for dealing with reaction time data. On the basis of the model's assumption that component mental processes are temporally successive, the mean reaction time observed in response to a presented test stimulus may be viewed as simply equaling the summed durations of those processes. Thus, if one accepts the serial-processing assumption, and if one makes certain other ancillary assumptions, one may formulate an interesting interpretation whenever two or more experimental factors have additive effects on mean reaction time (S. Sternberg, 1969). The interpretation, which grows out of S. Sternberg's (1969) additive-factor method, would be that each identified additive factor influences a different stage of processing and that performance entails at least as many stages as there are additive-factor effects. From the nature of the factors at hand, it may be possible to draw
detailed inferences about the inner workings of each processing stage.

Under some circumstances, the discrete stage model may also allow the absolute durations of component mental processes to be estimated. This estimation, which involves the subtraction method (Donders, 1868/1969; S. Sternberg, 1969), requires reaction time data from two tasks, A and B, that have certain special properties. In particular, the performance of Task A should entail a sequence of strictly successive mental processes (P₁, P₂, . . . , Pₙ), and the performance of Task B should likewise entail all of these processes, plus an additional process, Pₙ. The insertion of Pₙ as part of performing Task B must be "pure" in the sense that it does not alter the durations of the other processes (S. Sternberg, 1969). Then, because of the discrete stage model's additivity feature, one may estimate the absolute duration of the inserted process, Pₙ, by subtracting the mean reaction time of the inserted process, Pₙ, from the mean reaction time to perform Task A from the mean reaction time to perform Task B.

Many theorists have therefore adopted the discrete stage model enthusiastically and have applied it to analyze performance in a variety of cognitive tasks beyond those originally investigated by S. Sternberg (1969). The model has been used, for example, in interpreting the results of experiments on same-different letter matching (Posner & Mitchell, 1967), word recognition (Meyer et al., 1974, 1975; Rubenstein, Lewis, & Rubenstein, 1971), semantic-memory retrieval (Collins & Quillian, 1969; Meyer, 1970; E. E. Smith, Shoben, & Rips, 1974), sentence verification (Clark & Chase, 1972; Meyer, 1973, 1975; Trabasso, Rollins, & Shaughnessy, 1977), and analogical reasoning (R. J. Sternberg, 1977). Yet the notion of discrete serial processing has not completely enthralled everyone. Some opposing theorists have found S. Sternberg's (1969) discrete stage model to be implausible in light of current concepts about brain structure and neural mechanisms, so they have turned their attention toward models based on parallel processing and a continuous or quasi-continuous flow of information (e.g., Eriksen & Schultz, 1979; McClelland, 1979; Morton, 1969; Ratcliff, 1978; Rumelhart & McClelland, 1986).

Cascade Model

An instructive example of continuous parallel processing is embodied in McClelland's (1979) cascade model. In some respects, this model resembles S. Sternberg's (1969) discrete stage model. It assumes that responses to stimuli are mediated by a set of functionally ordered processes such as encoding, retrieval, decision, and response preparation, through which information passes unidirectionally (see Figure 2). In other respects, however, the cascade model differs considerably from the stage model regarding the temporal organization of component processes and the transmission of their outputs. All processes operate concurrently (i.e., in parallel) under the cascade model, and information flows continuously in the form of an increasing "spread of activation" (cf. Meyer & Schvaneveldt, 1971, 1976). Given a particular level of activation as input, each process supposedly produces a negatively accelerated output over time, with an exponential rate parameter and positive asymptote. Thus, when a stimulus is presented, activation gradually increases throughout the whole system until a threshold is crossed in a final response-selection process, triggering an overt physical movement.

The assumptions of the cascade model endow it with some interesting properties for interpreting reaction time data. Within the model's theoretical framework, the absolute duration of a component mental process cannot be estimated by using the subtraction method (cf. Donders, 1868/1969; S. Sternberg, 1969). Mean reaction time would not equal the summed durations of all the processes, because the processes are not strictly successive (McClelland, 1979). Nevertheless, the additive effects of various factors on mean reaction time might still be meaningfully interpreted. McClelland (1979) has shown that additivity would arise under the cascade model when two or more factors selectively influence the rate parameters of different processes. Analyses of additive-factor effects could therefore allow one to infer the existence and nature of functionally distinct processing components despite their temporal overlap.

The cascade model also provides meaningful interpretations for cases in which two or more factors have interactive rather than additive effects on mean reaction time. Consider a positive interaction, for example, where increasing the level of one factor (e.g., stimulus degradation) magnifies the effect that is due to another factor (e.g., semantic relatedness), as found in some studies of word recognition (Meyer et al., 1975). McClelland (1979) has shown that such a pattern could arise if the rate parameter of one process and the base-level activation or asymptote parameter of another process are affected selectively by two factors. Depending on exactly which parameters of the processes are involved, the cascade model may yield various interactive patterns, even though the factors used to manipulate those parameters do not directly influence the same component process.

This last point highlights another major difference between the cascade model and the discrete stage model. As mentioned already, the discrete stage model implies that if two factors selectively influence separate processing stages, they should have additive effects on mean reaction time (S. Sternberg, 1969).

For example, suppose that a process has rate and asymptote parameters denoted by r and a, respectively. Then with a unit input of activation, the process would produce an output activation level, A(t), such that \( A(t) = a(1 - e^{-rt}) \), where \( r \) represents the amount of time since the input began, and \( e \) is the base of natural logarithms.
Thus, applying the logic of modus tollens (i.e., if \( p \), then \( q \); not \( q \); therefore, not \( p \)), the natural interpretation of an interaction between factor effects under the stage model would be that the factors influence the same processing stage. Under the cascade model, however, an interaction could arise from two factors that influence the parameters of functionally distinct processes.

The different treatments of factor interactions by the cascade and discrete stage models may lead to significant substantive conflicts in assessing the detailed operations of particular mental processes. In their study of word recognition, for example, Meyer et al. (1975) asked subjects to perform a lexical-decision task in which the subjects judged whether various strings of letters were English words or nonwords. The subjects responded faster to a word (e.g., \textit{butter}) when it was preceded by another semantically related word (e.g., \textit{bread}) than when it was preceded by an unrelated word (e.g., \textit{nurse}). A larger semantic-relatedness effect occurred when the words were visually degraded than when they were presented intact. Assuming that word recognition can be characterized by a discrete stage model, Meyer et al. (1975) interpreted the obtained interaction between semantic relatedness and visual degradation to mean that both of these factors directly influence an early stimulus-encoding process. If this conclusion were valid, it would suggest that the effects of semantic relatedness, a seemingly "central" factor, may extend to relatively peripheral parts of the human information-processing system and that operations within the encoding process are highly context sensitive. Yet such a conclusion would not be warranted from the perspective of the cascade model (McClelland, 1979). Had Meyer et al. (1975) adopted the latter alternative to interpret their results, they might have reached a different conclusion. It is possible that visual degradation influences the rate parameter of a continuous parallel encoding process but that semantic relatedness does not influence encoding per se. Rather, the relatedness effect could merely alter the base-level activation of a concurrent retrieval process that receives input from the encoding process, thereby producing an indirect interaction with the visual-degradation factor (McClelland, 1979).

**Stochastic Diffusion Model**

Another instructive example of continuous information processing is embodied in the stochastic diffusion model formulated by Ratcliff (1978, 1988). Like the discrete stage and cascade models, the stochastic diffusion model assumes that processing may include components such as stimulus encoding, retrieval, decision, and response preparation. The heart of the model is a decision process that entails a gradual stochastic change in response strength over time, depending on the category to which a given test stimulus belongs.

For example, Figure 3 illustrates the nature of the assumed decision process when there are two stimulus categories, positive and negative. Here the horizontal axis represents the passage of time relative to the onset of a test stimulus. The vertical axis represents a strength variable used for deciding what response to initiate. At stimulus onset, the response strength is set to some initial base level, \( s_0 \). Subsequently, the response strength (solid jagged functions) starts to drift in either an upward or downward direction toward one of two threshold levels (horizontal dotted lines), whose distances above and below the base level are, respectively, \( d_p \) and \( d_n \). If the test stimulus is positive, then the direction of the drift would be biased toward the upper threshold; otherwise, it would be biased toward the lower threshold. Thus, the drift of response strength in the stochastic diffusion model serves a function analogous to the spread of activation in the cascade model (cf. McClelland, 1979).

Unlike the cascade model, however, the stochastic diffusion model assumes that the response-strength drift over time is a random process, not a deterministic one. Even when a positive test stimulus has been presented, the response strength may occasionally drift downward as opposed to upward, and it may repeatedly reverse directions along the way before reaching one of the two threshold levels. If a negative test stimulus has been presented, then conversely, some occasional periods of upward rather than downward drift may occur.

Given that the test stimulus biases the drift of response strength, a tendency will exist to cross the upper threshold when the stimulus is positive and to cross the lower threshold when the stimulus is negative. However, incorrect responses can arise by chance because the randomness of the drift may occasionally lead it all of the way to the wrong threshold. For both correct and incorrect responses, the ultimate reaction time will depend on how long the drift process takes to reach threshold. In essence, the stochastic diffusion model constitutes the continuous analog of a discrete random-walk model (Ratcliff, 1978, 1988).
Figure 3. Stochastic diffusion model of information processing (Ratcliff, 1978, 1988).

It also resembles several other stochastic models of reaction time (e.g., Audley, 1960; Edwards, 1965; LaBerge, 1962; Lam-...
investigators have attempted to observe the intermediate processes and products of cognition by combining reaction time measures with batteries of psychophysiological measures, such as cortical evoked potentials and electromyographic activity (Coles et al., 1985). An advantage of this approach is that it provides glimpses at the neural events that underlie information processing; some disadvantages are that it requires sophisticated recording equipment and tentative, perhaps questionable, assumptions about the functional significance of those events. In other cases, investigators have taken a less direct approach, drawing inferences from detailed quantitative analyses of reaction time distributions or error rates on the basis of mathematical assumptions from signal-detection theory (Pachella et al., 1978; Reed, 1976, 1977; E. A. C. Thomas & Myers, 1972; cf. Green & Swets, 1966). This avoids the practical and theoretical complexities posed by physiological-recording techniques, but it has the disadvantage that the assumptions used instead may themselves be implausible or difficult to test (Krantz, 1969; Luce, 1963). With alternative assumptions of at least equal plausibility, quite different conclusions might emerge about information-processing dynamics.

To illustrate such difficulties, we will consider three specific ways of examining the dynamics of information processing in more detail. The first involves quantitative analyses of distributions from conventional reaction time experiments (Luce, 1986; S. Sternberg, 1969; Townsend & Ashby, 1983). The second deals with results from certain types of response-priming procedures (Meyer et al., 1984; Meyer, Yantis, Osman, & Smith, 1985; J. Miller, 1982a). And the third concerns speed-accuracy trade-off curves obtained through modifications of conventional reaction time procedures (Pachella, 1974; Wickelgren, 1977). Following our survey, we will introduce a new technique that may help to overcome some limitations of these preceding ones.

### Quantitative Analyses of Reaction Time Distributions

In developing the additive-factor method, S. Sternberg (1969) devoted considerable attention to inferences derived from the means of reaction times. He argued that under a discrete stage model with relatively minimal extra assumptions, one would expect two factors to have additive effects on reaction time means whenever those factors influence different stages of processing. As we have seen already, however, a similar prediction is made by at least some continuous parallel-process models (McClelland, 1979). The occurrence of factor additivity in reaction time means does not necessarily distinguish one type of model from another.

Nevertheless, distributions of reaction times have other quantitative features that, under some circumstances, may allow various models of information processing to be tested. For example, suppose the performance of a cognitive task entails a sequence of temporally separate processes whose durations are stochastically independent. Suppose also there are two factors that selectively influence different components of this sequence. Then it is possible to test the discrete stage model by examining higher order moments of reaction time distributions, such as those associated with variance, skewness, and kurtosis. The specified factors should affect all distributional moments additively, if the stage model is valid. On the other hand, continuous parallel processes like those embodied in McClelland's (1979) cascade model would have difficulty accounting for such extended additivity.

An additional related test can be obtained if one makes specific assumptions about how the durations of component processes are individually distributed (Christie & Luce, 1956; Hohle, 1965; McGill, 1963; Ratcliff & Murdock, 1976; S. Sternberg, 1969). A useful illustration of this appears in the work of Hockley (1984). Following some previous theorists (e.g., Hohle, 1965; Ratcliff & Murdock, 1976), he assumed that the performance of various cognitive tasks (e.g., visual search, memory search, and recency judgment) includes two discrete serial stages with stochastically independent durations, in which the duration of one process has a normal distribution and the duration of the other has an exponential distribution. This assumption allowed him to predict the overall shapes of observed reaction time distributions. His results supported these predictions derived from the discrete stage model. It seems unlikely that an alternative model formulated in terms of continuous parallel processing could have done this well.

The problem with such analyses of reaction time data is that the assumptions on which they rest are fairly tenuous. Interpretations of higher order moments and exact shapes of reaction time distributions typically assume stochastic independence between stage durations (S. Sternberg, 1969). They also assume that the components of the distributions come from particular families (e.g., exponential or Gaussian). Violations of these assumptions, which might occur for unimportant reasons, could lead to rejecting a discrete serial-process model, even though performance does involve successive stages and discrete outputs (S. Sternberg, 1969). Consequently, other complementary approaches should be taken to analyze the time course and intermediate products of rapid information processing.

### Response-Prim ing Procedure

A second approach to such analyses has used various versions of a response-priming procedure. In this procedure, reaction times are measured under conditions in which subjects receive some advance partial information about a required response before they actually have to produce the response. From observing how the partial information primes performance, conclusions may be reached about characteristics of information-processing dynamics.

**J. Miller's study.** The utility of the response-priming procedure is illustrated in a study by J. Miller (1982a). During this study, subjects produced keypresses with the index and middle fingers of each hand as responses to stimulus letters displayed on a CRT screen. The assignment of the letters to the response fingers varied systematically across conditions. In one condition, letters like E, F, O, and Q were assigned, respectively, to the left index, left middle, right index, and right middle fingers. This assignment associated letters that had similar visual features (e.g., horizontal and vertical lines) with fingers on the same hand (e.g., left index and left middle). In another condition, there was no simple feature-to-hand correspondence. Reaction times were measured as a function of the different stimulus-response assignments.
The rationale of J. Miller's (1982a) study follows from previous work by Rosenbaum (1980), who investigated the motor programming of manual responses. Rosenbaum's (1980) results suggested that response preparation may entail an ordered specification of parameters associated with several physical and anatomical dimensions, such as the hand (right vs. left), finger type (index vs. middle), and movement distance needed for a response. Given this possibility, J. Miller (1982a) reasoned that if the response hand must be selected by a subject before the required finger type is selected, and if response preparation can begin before letter identification has ended, then varying the assignments of letters to finger keys should affect reaction times significantly. For example, an assignment with similar visual features all mapped onto the same hand would allow selection of the response hand to begin as soon as those features have been extracted, even though letter identification is not yet completed and selection of the required finger type has to wait somewhat longer. The advance response preparation would, in turn, reduce the overall reaction time compared with other conditions in which a heterogeneous assignment of visual features across hands does not permit preparation to begin until letter identification has been completed.

J. Miller's (1982a) study revealed such a reaction time reduction as a function of the feature-to-hand assignment. This outcome was confirmed in several experiments with various stimuli (e.g., straight and curved letters, small and large letters, letters and digits). Consequently, J. Miller inferred that letter identification and response preparation are parallel processes and that the preparation process can begin as soon as the identification process has provided it some requisite partial input, even though the preparation process selects the dimensions of a response serially. In essence, his results suggest a hybrid model incorporating both serial and parallel processing.

Still, there are some inherent limits to these conclusions and the response-priming procedure on which they rest. We do not know yet whether the procedure or conclusions would extend beyond situations in which an experimenter already has a firm idea about what the critical stimulus features and response dimensions are. Also, J. Miller's (1982a) results do not directly address whether the partial outputs of processes like letter identification occur as discrete packets or as a continuous flow of information over time. To address this latter issue, one must either extend the response-priming procedure or seek other complementary methods.

**Meyer et al.'s study.** A further extension of the response-priming procedure appeared in a study by Meyer et al. (1984; Meyer, Yantis, Osman, & Smith, 1985). This study was designed specifically to explore whether component mental processes have discrete or continuous internal states and outputs. To address the discrete-versus-parallel distinction, Meyer et al. (1984; Meyer, Yantis, Osman, & Smith, 1985) performed detailed quantitative analyses of reaction time distributions for unprimed, partially primed, and completely primed responses.

The reaction times came from a dual-stimulus version of the response-priming procedure. On each trial of the procedure, subjects first received a prime stimulus, which consisted of either an English word (e.g., tree), a nonword (e.g., mqed), or a neutral row of four Xs displayed on a CRT screen. The prime stimulus remained visible for either a medium or long duration. Subjects were instructed to assess the lexical status of the prime stimulus as best possible, but not to respond overtly to it. Following the offset of the prime stimulus, a test stimulus was presented immediately. The test stimulus consisted of a horizontal arrow that pointed either leftward (i.e., ←) or rightward (i.e., →). The subjects had to respond to the test stimulus as quickly and accurately as possible, pressing either a right index-finger key or a left index-finger key, depending on the direction of the arrow. There was a systematic contingency between the direction of the arrow and the lexical status of the preceding prime stimulus. Right arrows always followed word primes, and left arrows always followed nonwords. This allowed subjects to use the prime stimulus for preparing their response to the test stimulus, thereby reducing reaction times measured from the onset of the test stimulus. The neutral (XXXX) prime stimuli were followed equally often by right and left arrows, precluding any advance response preparation for them.

Meyer et al. (1984; Meyer, Yantis, Osman, & Smith, 1985) measured the subjects' reaction times as a function of the prime-stimulus type (informative words and nonwords vs. uninformative Xs) and the duration of the prime stimulus. The long prime-stimulus duration, which lasted 700 ms, permitted subjects to determine completely the lexical status of the prime stimulus and to reduce their reaction times by about 100 ms on average when the prime stimulus was informative (i.e., a word or nonword). A staircase tracking algorithm (Levitt, 1971) adjusted the medium prime-stimulus duration to a smaller value such that when the prime stimulus was informative, it yielded a priming effect (reaction time reduction) of about 50 ms, approximately half the one obtained with the long prime-stimulus duration. In effect, the prime stimulus with the medium duration allowed subjects to become partially, but not completely, prepared for the test stimulus.

The goal here was to determine whether subjects processed the prime stimuli in a discrete or continuous fashion. To achieve this goal, Meyer et al. (1984; Meyer, Yantis, Osman, & Smith, 1985) exploited the concept of a mixture distribution (Everitt & Hand, 1981; cf. Falmagne, 1968; S. Sternberg, 1973). They reasoned that if advance response preparation based on the prime stimuli involved a process with a discrete all-or-none output, then the reaction time distribution obtained in the partially primed condition (i.e., the condition in which informative primes had a medium duration) should be a simple probabilistic mixture of the other two distributions obtained, respectively, in the completely primed condition (i.e., the condition in which informative primes had a long duration) and the unprimed condition (i.e., the condition in which neutral primes were presented). This prediction assumes that the subject either enters a discrete fully prepared state or remains in an initial unprepared state, depending on exactly how long it takes to identify the prime stimulus and select the anticipated response. On the other hand, a higher order (i.e., more than two-state) discrete or continuous model would not make such a mixture prediction.

Meyer et al.'s (1984; Meyer, Yantis, Osman, & Smith, 1985) results supported the mixture prediction made by a discrete two-state (all-or-none) model of response preparation. Figure 4 shows an idealized plot of their results. They found that the reaction time distribution (probability-density function) in the partially primed condition, \( f_d(t) \), was well fit by a simple proba-
Figure 4. Mixture distributions of reaction times predicted by a two-state discrete model of response preparation (from Meyer, Yantis, Osman, & Smith, 1985). (The distribution in the partially primed condition—middle panel—is a perfect mixture of the distributions in the unprimed—top panel—and completely primed—bottom panel—conditions, reflecting the probabilistic contributions of an unprepared and a fully prepared state.)

We do not mean to imply, however, that human information processing is always discrete or that the response-priming procedure yields a general picture of information-processing dynamics. Some idiosyncrasies of this procedure as used by Meyer et al. (1984; Meyer, Yantis, Osman, & Smith, 1985) limit the extent of their conclusions. For example, the prime and test stimuli presented there came respectively from different domains (i.e., verbal and pictorial) and were displayed successively rather than as a unified gestalt (cf. J. Miller, 1982a). The selection and temporal arrangement of stimulus types could have induced a discrete processing strategy, whereas other procedures might induce a continuous strategy. This latter possibility

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We do not mean to imply, however, that human information processing is always discrete or that the response-priming procedure yields a general picture of information-processing dynamics. Some idiosyncrasies of this procedure as used by Meyer et al. (1984; Meyer, Yantis, Osman, & Smith, 1985) limit the extent of their conclusions. For example, the prime and test stimuli presented there came respectively from different domains (i.e., verbal and pictorial) and were displayed successively rather than as a unified gestalt (cf. J. Miller, 1982a). The selection and temporal arrangement of stimulus types could have induced a discrete processing strategy, whereas other procedures might induce a continuous strategy. This latter possibility
Figure 5. A continuous speed-accuracy trade-off curve (top panel) and an underlying discrete all-or-none process (bottom panel) with variable transition times that could produce this curve.

is supported by a study of Yantis and Meyer (1985, 1988), who found evidence for more than two preparatory activation states with prime and test stimuli that were semantically related words from the same verbal domain. More work is therefore needed to determine exactly when discrete and continuous processes mediate the performance of various cognitive tasks.

Speed-Accuracy Trade-off Methodology

A third approach to investigating the internal states and outputs of component mental processes relies on speed-accuracy trade-off methodology (Ollman, 1977; Pachella, 1974; Reed, 1976; Wickelgren, 1977). During an experiment with this methodology, subjects are encouraged to trade accuracy for speed of performance, producing systematic variations of mean reaction times and error rates across conditions. The trade-off may be induced by using feedback and payoffs that differentially reward either short reaction times or low error rates (Dickman & Meyer, 1988; Edwards, 1965; Fitts, 1966; Swenson & Edwards, 1971). Other ways of inducing the trade-off involve either imposing subjective deadlines on reaction times (Ollman & Billington, 1972; Pachella & Pew, 1968; Snodgrass, Luce, & Galanter, 1967) or presenting peremptory response signals that mandate action at various moments following the onset of a test stimulus (Reed, 1976; Schouten & Bekker, 1967). As a result, a trade-off curve is obtained that represents the accuracy of performance versus the amount of time allowed to process the test stimulus.

The top panel of Figure 5 illustrates a typical speed-accuracy trade-off curve. Several qualitative features of this curve should be noted. At some early point in time after the test stimulus has appeared, accuracy starts to increase above an initial base level. At some later time point, accuracy converges toward a much higher asymptotic level. Between these two points, the increase of accuracy proceeds gradually, extending over a considerable period of time.

Given that the speed-accuracy trade-off curve has such features, a number of theorists have interpreted it in terms of continuous-processing models (e.g., McClelland, 1979; Ollman, 1977; Ratcliff, 1978, 1988; Reed, 1976; Wickelgren, 1977). This interpretation seems quite reasonable. The shape of the curve looks similar to what might be expected from a cascade of gradually activated processes (McClelland, 1979), a stochastic diffusion of response strength (Ratcliff, 1978), or some other mechanism with continuous internal states and outputs. For example, one could view the asymptote to which accuracy eventually rises as reflecting the peak activation level of a processing system, and one could view the intermediate slope as reflecting the rate at which activation increases over time (McClelland, 1979; Wickelgren, 1977). The speed-accuracy trade-off curve’s smooth form provides no solace for models that incorporate discrete internal states and quantal outputs.

Even so, theoretical interpretations drawn from typical speed-accuracy trade-off curves, like those provided by the other approaches outlined earlier, rest on tenuous assumptions. If the speed-accuracy trade-off is interpreted in terms of a continuous-processing system, it must be assumed that subjects accumulate activation or information steadily until the moment action is initiated in response to task demands. A transitory pause in midstream or a premature termination of processing ahead of the experimenter’s appointed time would violate this assumption, leaving doubt about how the accumulation actually takes place (Meyer & Irwin, 1981). Furthermore, accommodating to the experimenter’s demands for more speed at the expense of less accuracy may alter the subjects’ mode of processing from what would be adopted under the conditions of conventional reaction time procedures.

There are also other, more serious problems with this methodology. The responses that contribute to typical speed-accuracy trade-off curves may stem from a confounded mixture of different internal states and information levels. As a result, they may actually obscure the presence of intermediate processes that have discrete internal states and produce quantal outputs of information (Meyer & Irwin, 1981; Schmitt & Scheirer, 1977; cf. Dosher, 1979). For example, suppose processing does not involve a continuous partial-information flow, but is mediated instead by a simple two-state discrete mechanism with an all-or-none output of information. Then despite the simplicity of this latter alternative, a smooth monotonically increasing speed-accuracy trade-off curve like the one in the top panel of Figure 5 would still emerge.

The bottom panel of Figure 5 illustrates how this might happen. Here the solid step function represents a simple abrupt transition in the amount of information accumulated over time, jumping from a discrete state of no information to a discrete state of high information about the correct response to a presented test stimulus. The dashed function represents a hypothetical distribution of times at which the transition may occur after the stimulus has been presented. If the transition-time distribution has an appropriate shape, and if data are averaged across trials, then a continuous speed-accuracy trade-off curve would result even though the underlying process is really discrete. The situation is reminiscent of one that confronted theorists when they sought to use smooth average learning curves...
for testing all-or-none versus incremental models of paired-associate learning (Bower, 1961; Estes, 1964). 3

Implications for Model Testing

Our survey of available approaches to analyzing rapid human information processing suggests that many significant issues remain unresolved. Analyses based on reaction time procedures and speed-accuracy trade-off methodology have not yielded data sufficient for definitive tests between discrete serial-process models and continuous parallel-process models. Conventional reaction time procedures are limited because they provide direct evidence only about the overall duration and accuracy of several processes in combination. Without tenuous ancillary assumptions, they do not permit insights into the durations or intermediate products of individual processing components. Standard speed-accuracy trade-off methodology and other related techniques constitute an intriguing attempt to overcome these difficulties, but they, too, suffer from some serious limitations. The situation is concisely summarized by the following quote from a leading authority in the field (Wickelgren, 1977, p. 79):

At present, I know of no results that would distinguish which of these very general classes of theories [i.e., discrete and continuous models of information processing] is correct. In analogous situations in perception and memory, it has proven extremely difficult to distinguish between discrete and continuous theories by any simple set of experimental observations. . . . Based on past experience, it seems doubtful that we can definitely decide between these broad classes of theories in the near future.

Clearly, additional work must be done on developing more powerful approaches with which to assess the temporal relations, internal states, and output characteristics of information-processing components.

Speed-Accuracy Decomposition Technique

The present article describes a further approach developed in our laboratory for analyzing the intermediate products of rapid mental processes. We call this approach the speed-accuracy decomposition technique. Speed-accuracy decomposition is designed for use under conditions that, in some respects, resemble those of conventional reaction time procedures, in which subjects must produce highly accurate responses to stimuli as quickly as a strict accuracy requirement permits. The technique also incorporates some key features of standard speed-accuracy trade-off methodology. This allows us to measure the amount of partial information that has been accumulated up to any particular moment in processing a presented stimulus before a response to the stimulus occurs. As argued already, such information cannot be measured through conventional reaction time procedures alone, because they reveal only the overall accuracy and duration of several component mental processes in combination. Nor does standard speed-accuracy trade-off methodology solve the measurement problem, because it may suffer from transitory pauses or premature termination in subjects' processing, and it may obscure the presence of discrete internal states or outputs (Figure 5). However, by joining these previous approaches in a unified empirical and theoretical framework, speed-accuracy decomposition provides a way to alleviate their individual limitations.

Figure 6 outlines the principal focus of speed-accuracy decomposition in more detail. Here we have illustrated three alternative patterns that subjects might exhibit as they accumulate information for responding to a presented stimulus during a conventional reaction time procedure. The horizontal axes represent the amount of time elapsed since stimulus onset. The vertical axes represent the amount of information accumulated through some set of component mental processes. In this context, the term information has a meaning similar to that defined by mathematical communication theory (Shannon, 1948); it quantifies the contributions of internal processing states and outputs that directly increase stimulus certainty and response accuracy (cf. Garner, 1962). 4 The accumulation of information over time is represented by the solid functions. We assume that response selection is initiated when the accumulated information reaches a specified high threshold indicated by the horizontal dotted lines. Consequently, excluding the duration of response-selection and execution processes, reaction time is given by the solid horizontal arrows.

What differs among the panels of Figure 6 is the path taken in reaching the threshold level of information needed for initiating a response. According to the top panel, a subject starts to process a stimulus from an initial state of minimal information about its identity and about the correct response to it. As time passes, this state persists until a single discrete transition occurs into another state of high information, triggering the output of a (typically) correct response. Such a two-state discrete pattern is analogous to the one considered previously in discussing potential limitations of standard speed-accuracy trade-off methodology (Figure 5, bottom panel). The middle panel of Figure 6 generalizes this pattern. According to it, the accumulation of information over time involves a multiple, yet finite, number of discrete transitions between information states until the response-selection threshold is crossed. Lastly, the bottom panel of Figure 6 extends the aforementioned generalization even further. According to it, partial information accumulates in a continuous, gradually increasing fashion without any discrete transitions before crossing the threshold for response selection.

3 One way of trying to overcome this confounding might be to combine psychophysiological measures with overt behavioral variables such as response speed and accuracy. Coles, Gratton, Bashore, Eriksen, and Donchin (1985) have suggested, for example, that speed-accuracy trade-off curves conditioned on the latencies of underlying cortical evoked-potential components reveal the true time course of information processing. However, this approach still requires aggregating data across multiple trials, which could again cause smearing as in Figure 5 and obscure the presence of discrete internal states and outputs.

4 Of course, this is not the only sense in which we could use the term information. Some intermediate products of processing may be essential to the selection of a correct response and may constitute implicit information but may not increase response accuracy directly. For example, identifying the physical features of the letters in a string of alphabetic characters would help indirectly to decide whether the string is a word or nonword, even though identifying the features without proceeding further would not increase the accuracy of the decision (cf. McClelland & Rumelhart, 1981). Speed-accuracy decomposition must be augmented with other techniques to assess such contributions.
The objective of speed-accuracy decomposition is to obtain and analyze data regarding such alternative patterns of information accumulation. In particular, our efforts focus on those portions of the information-accumulation functions that lie below the response-selection thresholds (dotted horizontal lines) of Figure 6. As we will discuss later, this endeavor yields tests of competing models that make different assumptions about the nature of the internal states and outputs of component mental processes. Results from the decomposition technique can directly address the discrete-versus-continuous distinction for a variety of cognitive tasks, and they can also address the serial-versus-parallel distinction at least indirectly, given that discrete models are commonly associated with serial processing (e.g., Sternberg, 1969), whereas continuous models are commonly associated with parallel processing (e.g., McClelland, 1979).

Like other approaches discussed earlier, speed-accuracy decomposition does entail some specific assumptions. These assumptions are testable, however, and relatively innocuous compared with previous ones. For example, the decomposition technique can be applied in conjunction with cognitive tasks that involve many-to-one (Posner, 1964), not just one-to-one, stimulus–response assignments (cf. J. Miller, 1982a). Prior knowledge about subjectively relevant stimulus features and response dimensions is unnecessary (cf. Rosenbaum, 1980). The reaction times under consideration may come from various families of distributions; they are not required to have an exponential, gamma, or Gaussian form (cf. McGill, 1963). Also, no confidence ratings or receiver-operating-characteristic (ROC) curves from signal-detection theory are needed (cf. Reed, 1976, 1977; E. A. C. Thomas & Myers, 1972). During the remainder of this article, we describe more fully the details of speed-accuracy decomposition and the theoretical framework upon which it rests. The decomposition technique includes two major facets: a hybrid procedure for collecting reaction time and accuracy data under various levels of speed stress, and a special metamodel for analyzing these data to assess the accumulation of partial information over time. Each facet will be discussed in turn. Then some representative results will be reported from an initial application of speed-accuracy decomposition to the study of visual word recognition.

Titration Reaction Time Procedure

To apply the speed-accuracy decomposition technique, distributions of reaction times and patterns of response accuracy are first obtained with a hybrid procedure that involves a random mixture of two trial types: regular and signal. We call this the titrated reaction time (TRT) procedure. A sketch of it appears in Figure 7.

The TRT procedure has been developed with several criteria in mind. On the one hand, we wanted to induce a mode of performance in which subjects' processing of a presented test stimulus always starts with the intention of (a) quickly reaching a set high level of information about the correct response and then (b) immediately producing that response, as presumably happens in conventional reaction time procedures. On the other hand, we wanted to probe how partial information is accumulated during such performance, while avoiding the pitfalls of standard speed-accuracy trade-off methodology, in which responses may confound different information levels (e.g., Figure 5), unnecessary pauses may occur during processing, and processing may terminate prematurely.

Together, these criteria are satisfied by the combination of regular and signal trials used in the TRT procedure. The regular trials provide evidence about the duration and accuracy of processing under conditions in which a high threshold level of information is usually reached and a correct response is then immediately initiated. The signal trials complement the regular trials, providing evidence about the duration and accuracy of processing under conditions in which this threshold is not necessarily reached, but a response must be initiated anyway despite being potentially incorrect. It is in this sense that the procedure involves a kind of "titration." From comparing the results obtained with the two trial types, precise inferences are possible about the accumulation of partial information over time. Below we discuss each trial type in turn, and then we explain their joint rationale more fully.

Regular trials. On regular trials (Figure 7, top panel), the sequence of events is similar to what transpires in a conventional reaction time procedure. Each regular trial starts with a
brief warning signal. The warning signal is followed by a positive or negative test stimulus. For example, the positive stimuli might be printed words and the negative stimuli might be non-words, as in a lexical-decision task (Meyer & Schvaneveldt, 1971, 1976). Alternatively, the stimuli could consist of digits, sentences, pictures, or other sorts of items (e.g., see Kounios, Osman, & Meyer, 1987). Regardless of the domain from which the stimuli come, the subject must react to the test stimulus by making a corresponding positive or negative response (e.g., right or left key press) as soon as possible without committing many errors. Reaction time is measured from the onset of the test stimulus until the response, and the accuracy of the response is recorded. The subject receives feedback that encourages fast but highly accurate performance.\textsuperscript{5}

**Signal trials.** On signal trials (Figure 7, bottom panel), the sequence of events is also similar in some respects to what transpires in a conventional reaction time procedure. Each signal trial starts with a brief warning signal, followed by a positive or negative test stimulus. When the test stimulus appears, the subject must adopt a set toward making a correct positive or negative response while taking whatever time is needed to ensure a low error rate. As on regular trials, the subject is supposed to react as soon as enough information has been accumulated for a correct response. To help induce this mental set, the signal trials are mixed randomly with the regular trials so the subject cannot discriminate beforehand between the two trial types.

Subsequently, however, the signal trials are more like those commonly associated with speed–accuracy trade-off methodology. At some moment after the test stimulus has appeared, a peremptory response signal (e.g., auditory tone) is presented on each signal trial. The lag of the response signal (i.e., time between test-stimulus and response-signal onsets) may vary from trial to trial. If a response to the test stimulus has not been made by the time the response signal is presented, then upon detecting the response signal, the subject must make a positive or negative response immediately, indicating his or her best guess about what the correct response is. This guess may be based on any partial information accumulated up to the moment when the signal is detected. Subjects are reinforced both for reacting quickly to the response signal and for making correct responses despite the extra speed stress imposed on them. Reaction time is again measured from the onset of the test stimulus until the response occurs, and the accuracy of the response is recorded.\textsuperscript{6}

As a result, manipulation of the signal lag will yield an average speed–accuracy trade-off curve much like those from experiments involving standard speed–accuracy trade-off methodology (e.g., Figure 5, top panel), but with the new analysis outlined here, this curve can be decomposed to examine the accumulation of partial information more precisely than has been possible previously.

The decomposition of speed and accuracy is enabled by some key features of the signal trials that distinguish them from ones typically used in speed–accuracy trade-off methodology. In past experiments with response signals (e.g., Corbett & Wickelgren, 1978; Ratcliff & McKoon, 1982; Reed, 1976; Schouten & Bekker, 1967), a signal has been presented after a test stimulus on

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\textsuperscript{5}Although we describe the TRT procedure as if it involves only two types of test stimuli and responses (i.e., positive and negative), this is not a necessary restriction. There could be three or more stimulus and response types, yet the speed–accuracy decomposition technique would still apply.

\textsuperscript{6}The signal-trial reaction time is not measured from the onset of the response signal because, on some trials, a response may occur before we present the signal. Subjects do not have to withhold their responses until there is a signal. They may respond as soon as they have identified the test stimulus correctly.
In this context, the regular and signal trials serve complementary purposes. The purpose of the signal trials is to create a milieu in which some responses will be based on the below-threshold segments of the information-accumulation functions. Because these functions may vary from trial to trial, the signal-trial responses may also incorporate contributions from cases in which the accumulated information reaches threshold. The purpose of the regular trials is to account for such contributions. First, the regular trials establish the relevant threshold for initiating high-accuracy responses. Second, they provide benchmarks for evaluating subjects' performance on the signal trials. With regular-trial data as a reference, it is possible to assess exactly what proportions of the signal-trial responses come from below-threshold information and what proportions come from at-threshold information. It is also possible to assess the degree of response accuracy that can be achieved when the threshold is reached. Taking these measures into account, we may examine the pattern of partial information that subjects accumulate before reaching threshold. This lets us test discrete and continuous models that involve different information-accumulation functions.

Parallel Sophisticated-Guessing Model

For analyses of data from the TRT procedure, the speed–accuracy decomposition technique relies on a parallel sophisticated-guessing (PSG) model. The PSG model constitutes a “metamodel” in that it makes no assumptions about whether the internal states or outputs of component mental processes are discrete or continuous. Instead, the role of the PSG model is to establish a quantitative theoretical framework on whose basis the assumptions of other substantive models, such as the discrete stage model (S. Sternberg, 1969), cascade model (McClelland, 1979), and stochastic diffusion model (Ratcliff, 1978) can be tested regarding the discrete-versus-continuous distinction. After describing and validating the PSG model, we may use it to determine which account best characterizes the accumulation of partial information over time during the performance of a given cognitive task.

The PSG model incorporates and extends previous theoretical ideas about the temporal properties of complementary components in the human information-processing system (Kornblum, 1973; Logan & Cowan, 1984; Oilman & Billington, 1972; Osman, Kornblum, & Meyer, 1986). It assumes there are two parallel sets of processes that operate in various combinations, depending on whether a regular or signal trial of the TRT proce-

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7 Another complementary way of viewing the regular trials is to consider them as signal trials with an infinite signal lag. From this perspective, the TRT procedure may seem analogous to a conventional speed–accuracy trade-off procedure with variable response-signal lags. However, there are still important differences between the two types of procedures. For example, in the TRT procedure, subjects may react whenever they wish after a response signal has occurred, and if they always wait until a signal does occur, they would never respond on some trials (i.e., the regular ones). On the other hand, a conventional speed–accuracy trade-off procedure that uses response signals does not have these latter features (Reed, 1976), which are crucial for drawing inferences through speed–accuracy decomposition.
The parallel sophisticated-guessing model on which speed-accuracy decomposition is based.

**Normal processes.** The normal processes are depicted by the runner at the top of Figure 9. According to the PSG model, they start at the beginning of both regular and signal trials when a test stimulus is presented, and they finish by executing an overt response based on reaching a high threshold level of "complete" information about the identity of the test stimulus. This constitutes an essential component of the model. Because our instructions require responses to be extremely accurate on the regular trials, and because the regular trials are mixed randomly with the signal trials, a subject must approach every trial with the goal of responding correctly, in hopes that no response will occur and that processing will be finished successfully. Likewise, if there is temporal independence, the normal processes would not interfere with the progress of the guessing processes.

**Guessing processes.** The PSG model includes five basic assumptions about the guessing processes:

1. The guessing processes begin at the onset of a response signal.
2. The guessing processes entail detecting the response signal is involved. Some of these processes consist of ones that race with each other, and the observed data (i.e., reaction time and response accuracy) are determined by the winner of the race (i.e., the set of processes that finish first). Figure 9 illustrates the functional relation between the normal and guessing processes under the PSG model.

Normal processes. The normal processes are depicted by the runner at the top of Figure 9. According to the PSG model, they start at the beginning of both regular and signal trials when a test stimulus is presented, and they finish by executing an overt response based on having reached a high threshold level of "complete" information about the identity of the test stimulus. This constitutes an essential component of the model. Because our instructions require responses to be extremely accurate on the regular trials, and because the regular trials are mixed randomly with the signal trials, a subject must approach every trial with the goal of responding correctly, in hopes that no response signal will occur and that processing will be finished successfully. However, once a signal has occurred, the subject cannot simply wait until he or she finishes more processing to ensure a correct response. Instead, another complementary set of processes must enter the race and generate a rapid "best guess" about the correct response to the test stimulus. This is depicted by the guessing processes at the bottom of Figure 9.

Guessing processes. The PSG model includes five basic assumptions about the guessing processes:

1. The guessing processes begin at the onset of a response signal.
2. The guessing processes entail detecting the response signal on signal trials. We call them normal processes. Others consist of guessing processes induced by the response signal on signal trials after the normal processes have begun. On the signal trials, the two sets of processes (i.e., normal and guessing) supposedly temporally inde- pendently. We call this the temporal-independence assumption. It implies that the initiation and execution of the guessing processes do not terminate the normal processes prematurely or otherwise interfere with their progress toward successful completion. Likewise, if there is temporal independence, the normal processes would not interfere with the progress of the guessing processes.

5. If the guessing processes finish before the normal processes on a signal trial, then the observed reaction time and response are determined by the duration and output of the guessing processes; otherwise, overt performance is determined by the duration and output of the completed normal processes. We call this the winner-takes-all assumption.

These assumptions, which form the heart of the PSG model, may be validated in several ways. We can support some of them by examining the estimated durations of the guessing processes to see how they vary with the response-signal lag and the nature of the test stimuli. Other support comes from previous studies of performance in dual-task situations that resemble the TRT procedure in certain respects. For example, Hirst, Spellke, Reaves, Caharack, and Neisser (1980) have shown that after practice, subjects can perform simple dual tasks (e.g., signal detection and stimulus discrimination) without suffering significant disruption relative to a single-task control condition. In addition, parallel-process (race) models with assumptions similar to those of the PSG model have been used successfully for research on a variety of projects related to ours (e.g., Kornblum, 1973; Olman & Billington, 1972; Osman et al., 1986; cf. J. Miller, 1982b).

**Analyses Based on the PSG Model**

With the PSG model, it is possible to analyze several aspects of subjects' performance on regular and signal trials of the TRT procedure. One important aspect is the distribution of times at which the guessing processes finish and generate overt responses relative to the onsets of the test stimuli. We call these guessing-completion times. They are a joint function of several temporal variables, including the length of the signal lag, the time to detect the response signal after its onset, the time to evaluate any partial information provided by the normal processes to the guessing processes, and the time to execute a response based on that information. Another important aspect of performance is the probability that the guessing processes generate a correct response to the test stimulus when they win the assumed race with the normal processes. We call this the guessing accuracy. It presumably reflects the amount of partial information available to select a response before the normal processes have finished. Neither the guessing accuracy nor the guessing-comple-
tion times can be observed directly because of confounding caused by the normal processes occasionally beating the guessing processes on the signal trials. However, the guessing accuracy and the guessing-completion times can be estimated indirectly from the combination of reaction times and error rates obtained on the regular and signal trials.

Both of these estimates are of considerable interest. The estimated guessing accuracy bears directly on the distinction between discrete and continuous information processing. The estimated guessing-completion times provide tests of the PSG model's assumptions about the race between the normal and guessing processes. Also, the guessing-completion times play an important role in subsequent analyses of the guessing accuracy and of accumulated partial information. In what follows, we next discuss the estimation of the guessing-completion times. Then the estimation of the guessing accuracy is considered.

**Estimation of guessing-completion times.** A distribution of guessing-completion times may be estimated from the observed reaction times on the regular and signal trials. For any given response-signal lag (i.e., stimulus-onset asynchrony; SOA) and type of test stimulus, suppose that \( t_n \) and \( t_g \) are random variables denoting the regular-trial and signal-trial reaction times, respectively. Suppose also that \( t_n \) denotes the time taken to complete the normal processes, \( d_n \) denotes the duration of the guessing processes measured from the onset of the response signal, and \( t_g \) denotes the guessing-completion time. Then according to the PSG model, \( t_g = SOA + d_n \), and the probability that the signal-trial reaction time \( t_s \) exceeds a constant \( C \) is given by the following equation:

\[
P(t_s > C) = P(t_n > C) \text{ and } P(t_g > C) = P(t_n > C)P(t_g > C), \tag{1}
\]

where \( 0 < C < \infty \).

Equation 1 stems from several basic assumptions. Under the PSG model, the reaction time on a signal trial \( t_s \) will exceed \( C \) if and only if the completion times of the normal and guessing processes both exceed \( C \) (cf. Kornblum, 1973; Oilman & Billington, 1972). This is because the race between these sets of processes will not take longer than \( C \) to be won unless each of them takes longer than \( C \) to finish. The rules of the race lead us directly from the left side to the middle of Equation 1. Also, the duration of the guessing processes \( d_n \) and the guessing-completion time \( t_g \) are assumed to be independent of the completion time for the normal processes \( t_n \). Consequently, as the right side of Equation 1 indicates, the probability that both \( t_n \) and \( t_g \) exceed \( C \) is simply a product of the probabilities that each of these random variables exceeds \( C \) individually.

From Equation 1, an estimate can be derived for the probability that the guessing-completion time is less than or equal to \( C \) (Meyer & Irwin, 1981). According to the PSG model, reaction time \( t_s \) on the regular trials equals the completion time of the normal processes \( t_n \). Substituting this relation into Equation 1 along with the facts that \( P(t_s > C) = 1 - P(t_s \leq C) \), \( P(t_n > C) = 1 - P(t_n \leq C) \), and \( P(t_g > C) = 1 - P(t_g \leq C) \), we obtain Equation 2 after some simple algebraic rearrangement:

\[
P(t_g \leq C) = \frac{P(t_s \leq C) - P(t_n \leq C)}{1 - P(t_n \leq C)}. \tag{2}
\]

The left side of Equation 2 constitutes a cumulative distribution function, \( F_{gs}(C) \), of guessing-completion times (i.e., \( F_{gs}(C) = P(t_g \leq C) \)). The right side involves a combination of cumulative distribution functions, \( F_n(C) \) and \( F_g(C) \), associated with the signal-trial and regular-trial reaction times, respectively (i.e., \( F_n(C) = P(t_n \leq C) \) and \( F_g(C) = P(t_g \leq C) \)). Thus, because the latter functions are estimable from the data on the regular and signal trials, they let us estimate the former function (i.e., \( F_{gs}(C) \)) through Equation 2, thereby revealing the temporal properties of the guessing processes.\(^8\)

An illustration of what some representative time distributions would look like if the PSG model is valid appears in Figure 10. The figure contains hypothetical cumulative distribution functions of regular-trial reaction times \( F_n(C) \), signal-trial reaction times \( F_g(C) \), dashed function), and guessing-completion times \( F_{gs}(C) \), dotted function). These functions satisfy Equation 2 exactly. Consequently, one can show that they have special qualitative and quantitative relations to each other. In particular, the distribution of signal-trial reaction times begins rising at the temporal minimum of the other two distributions (i.e., regular-trial reaction times and guessing-completion times), and it continues upward more steeply than those distributions do. As we discuss later, such relations among the various distributions, which follow from the PSG model, may be checked empirically to test some of the model's basic assumptions.

**Estimation of guessing accuracy.** Our next step in speed-accuracy decomposition is to estimate the accuracy of the guessing processes. The guessing-accuracy estimates involve removing the contribution of the completed normal processes to the observed accuracy of responses on signal trials and then examining the residual that remains. This requires taking into account the estimated distribution of guessing-completion times discussed earlier (Equation 2).

According to the PSG model, a correct signal-trial response can occur in either one of two mutually exclusive ways: either the normal processes may finish before the guessing processes and produce a correct response, or the guessing processes may finish before the normal processes yet produce a correct response that is based on available partial information and luck. We can express the probability of a correct signal-trial response, \( P_{\text{S}}(\text{correct}) \), for a given test stimulus as follows:

\[^8\] Some other versions of the PSG model would also lead to the same results. In our formulation of the model, we assume that all components of the normal processes (e.g., encoding, retrieval, decision) may overlap temporally with all components of the guessing processes, including the production of overt physical movements. However, complete temporal overlap is not essential to the success of the model. For example, suppose that the guessing and normal processes only race up to a point at which a final response-execution stage begins (cf. Osman, Kornblum, & Meyer, 1986), and that only the winner of this truncated race proceeds to initiate a subsequent physical movement. Then Equation 2 could still hold. The only additional requirement for maintaining this equation would be that the duration of the final common output stage (i.e., response execution) should have a low (viz., zero) variance. Such low variance is consistent with empirical data from some studies of the motor mechanisms involved in movement production (Kristofferson, 1976).
when the normal processes have not yet finished. If the guessing accuracy exceeds a chance level (e.g., 50%), then we would infer that the normal processes produce some useful intermediate output(s) on the way to their eventual completion. Thus, by plotting the left side of Equation 4 as a function of signal lag (SOA) or mean guessing-completion time, we may assess the accumulation of partial information and evaluate alternative classes of discrete versus continuous models.

For example, suppose performance involves a single discrete (all-or-none) output of information as shown in Figure 5 (bottom panel) and Figure 6 (top panel). Then as the signal lag increases on signal trials, the increasing probability of correct responses should be attributable entirely to completed normal processes, and the guessing accuracy derived from Equation 4 after removing the contribution of the completed normal processes should remain at a chance level throughout the signal trials, regardless of the lag. In contrast, normal processes that produce multiple discrete outputs could yield an increasing accumulation of partial information and guessing accuracy with one or more intermediate plateaus (Figure 6, middle panel). Furthermore, some normal processes that produce continuous outputs would yield a gradual increase of partial information without such plateaus in guessing accuracy (Figure 6, bottom panel).

**Tests of the PSG Model**

The application of speed–accuracy decomposition to examine the accumulation of partial information rests on several basic assumptions of the PSG model. For present purposes, the most important ones are the winner-takes-all assumption, the temporal-independence assumption, and the full-access assumption. If any of these assumptions are seriously violated, then the decomposition technique would be suspect. It is therefore important to test the PSG model as best possible before drawing any strong conclusions from derived partial-information.

9 Under the PSG model, 

\[ P(t_n \leq t_{gs}) = \int_{0}^{t_{gs}} F_n(x) f_{gs}(x) dx, \]

where \( F_n(x) \) is the cumulative distribution function for normal processes, and \( f_{gs}(x) \) is the probability-density function for guessing processes. A discrete analog of this equation may be used in estimating \( P(t_n \leq t_{gs}) \) to any desired degree of precision. As part of the technique, an estimate of \( f(x) \) comes from Equation 2, and an estimate of \( F(x) \) comes from the observed reaction times on regular trials.

10 Under the PSG model, 

\[ P_n(\text{correct} | t_n \leq t_{gs}) = \int_{0}^{t_{gs}} P_n(\text{correct} | t_n \leq x) f_{gs}(x) dx, \]

where \( P_n(\text{correct} | t_n \leq x) \) is the probability that the normal processes produce a correct response, given that their completion time is less than or equal to \( x \). A discrete analog of this equation may be used to estimate \( P_n(\text{correct} | t_n \leq t_{gs}) \) to any desired degree of precision. As part of the technique, an estimate of \( f_{gs}(x) \) comes from Equation 2, whereas the observed error rates and reaction times on the regular trials yield an estimate of \( P_n(\text{correct} | t_n \leq x) \). In particular, for any value of \( x \), the estimated value of \( P_n(\text{correct} | t_n \leq x) \) depends on the relative frequencies of correct and incorrect regular-trial responses whose latencies do not exceed \( x \).
tion accumulation functions. Fortunately, each of the model's assumptions can be tested at least indirectly with data obtained through the TRT procedure.

**Winner-takes-all and temporal-independence assumptions.** One simple test of the winner-takes-all and temporal-independence assumptions involves applying Equation 2, which is a manifestation of the hypothesized race between the normal and guessing processes. According to the PSG model, entering reaction times from regular and signal trials into the right side of Equation 2 should yield a legitimate cumulative distribution of guessing-completion times, as illustrated by the dotted function in Figure 10. The guessing-completion time distribution should start at a value of zero and rise steadily toward a value of one as time increases. However, real data need not conform to these constraints if the PSG model is invalid. Violations of the winner-takes-all or temporal-independence assumptions could produce observed signal-trial and regular-trial reaction times that, when entered into Equation 2, yield an illegitimate distribution of guessing-completion times. The distribution might, for example, exhibit nonmonotonics or never reach one (cf. J. Miller, 1982b).

More specifically, the reaction times on signal and regular trials must have a special relation for Equation 2 to yield a legitimate cumulative distribution of guessing-completion times. This relation may be expressed in terms of hazard functions (Bloxom, 1984; Luce, 1986; McGill, 1963). The hazard function of a random variable x is defined as

$$H(x) = \frac{f(x)}{[1 - F(x)]},$$  \hspace{1cm} (5)

where f(x) is the probability-density function of x, and F(x) is the corresponding cumulative distribution function. H(x) represents the probability density associated with a given value of x, conditioned on x equaling or exceeding that value. As formulated here, the PSG model implies that the theoretical hazard function of the signal-trial reaction times should never be less than the theoretical hazard function of the regular-trial reaction times (i.e., $H_s(x) \geq H_r(x)$). Furthermore, the hazard function of the signal-trial reaction times should exceed the hazard function of the regular-trial reaction times in any temporal interval in which the underlying completion times for both the guessing and normal processes have positive probability densities (Luce, 1986). We call this property hazard-function dominance. If it is not satisfied by the signal-trial reaction times relative to the regular-trial reaction times, then Equation 2 will not yield a legitimate cumulative distribution of guessing-completion times.

We should stress that deriving a legitimate cumulative distribution of guessing-completion times with Equation 2 constitutes more than just a check of whether the response signals have some effect on signal-trial performance. The response signals could conceivably speed subjects' responses without satisfying the requirement of hazard-function dominance. For example, consider Figure 11. In the top panel of the figure, we have plotted three hypothetical cumulative distributions. One represents a distribution for reaction times on regular trials (solid function), and one represents a distribution for reaction times on signal trials (dashed function). Both of these distributions increase monotonically from zero to one. The signal-trial distribution always equals or exceeds the regular-trial distribution, indicating that the response signal significantly reduces the magnitudes of the reaction times on signal trials, as might be expected with the TRT procedure. However, the distributions in the top panel of Figure 11 do not satisfy hazard-function dominance. At an intermediate point on the time scale, the hazard function of the regular-trial reaction times starts to exceed the hazard function of the signal-trial reaction times. This relation is illustrated in the bottom panel of Figure 11, which shows the corresponding hazard functions for the regular-trial reaction times (solid function) and signal-trial reaction times (dashed function), respectively. Given these hazard functions, an illegitimate cumulative distribution of guessing-completion times would be derived from applying Equation 2.

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11 Hazard-function dominance stems from the fact that if the signal-trial reaction times involve a race between two temporally independent sets of processes, namely, the normal and guessing processes, then the hazard function of those times will equal the sum of the hazard functions associated with each set (i.e., $H_s(x) = H_n(x) + H_g(x)$; Luce, 1986). In effect, adding more competition (i.e., the guessing processes) to race with the normal processes on the signal trials will increase the conditional probability density of a signal-trial response at time t, given that a response has not been observed already before time t. The additional competition should either reduce the time taken to win the race or leave it unchanged, not increase the winning time.
This illegitimacy is indicated by the dotted function in the top panel of Figure 11, which represents Equation 2's estimate for the cumulative distribution of guessing-completion times.\textsuperscript{12} The latter distribution dips down toward zero after reaching an intermediate value of about .5, and it never rises thereafter to a value of one. Correspondingly, the hazard function of the estimated guessing-completion times is negative for an intermediate range of time values (.53 \leq t \leq .55).\textsuperscript{13} If we found such a result in applying the speed–accuracy decomposition technique to real data, then the winner-takes-all or temporal-independence assumptions of the PSG model could be rejected. So deriving a legitimate cumulative distribution of guessing-completion times, as illustrated by the dotted function in Figure 10, provides a first level of support for the model and its assumptions.

A more stringent test of the winner-takes-all and temporal-independence assumptions involves examining the effects of signal lag on derived distributions of guessing-completion times. Suppose that we conduct a study with several different lags between the test stimuli and response signals on the signal trials of the TRT procedure. Also, suppose that (a) the signal lag does not affect the duration of the guessing processes, (b) the durations of the guessing and normal processes are stochastically independent, so the temporal-independence assumption holds, and (c) performance is determined by whichever set of processes finishes first, so the winner-takes-all assumption holds. Then according to the PSG model, as embodied in Equation 2, the derived cumulative distributions of guessing-completion times ought to exhibit the systematic pattern illustrated in Figure 12. They should have central tendencies (e.g., medians and means) that differ by the same amounts as the signal lags do. Moreover, the shapes of the distributions should be the same across all lags for which the induced guesses are always completed earlier than the maximum time taken by the normal processes. This is because the guessing-completion times suppose that equals the magnitudes of the signal lags plus the durations of the guessing processes, and the guessing processes would progress at the same rate regardless of when they take place relative to the prevailing normal processes. On the other hand, if the derived distributions of guessing-completion times have central tendencies that differ by much more or less than the differences between the signal lags, then this would raise serious doubts about the assumptions of the PSG model. Doubts would also arise from marked changes in the shapes of these distributions as a function of signal lag. Failures of either the winner-takes-all or the temporal-independence assumption could produce such changes.\textsuperscript{14} Consequently, it is worth looking carefully at the effects of signal lag on estimated guessing-completion times for support of these assumptions.\textsuperscript{15}

Another stringent test of the winner-takes-all and temporal-independence assumptions involves examining whether variations among test stimuli affect the derived distributions of guessing-completion times. This test is analogous to the preceding one based on signal-lag effects. In particular, suppose that we conduct an experiment with two or more types of test stimuli (e.g., positive and negative) and that stimulus type affects the completion times of "normal" processes on regular and signal trials. The normal processes might, for example, be completed more quickly with positive stimuli than with negative stimuli. Suppose also that the durations of the guessing processes are not affected by stimulus type and that the temporal-independence and winner-takes-all assumptions hold. Then despite the stimulus-type effects on the completion times of the normal processes, the distributions of guessing-completion times derived from Equation 2 in terms of regular-trial and signal-trial reaction times should have central tendencies and shapes that are invariant with stimulus type. An absence of such invariance would cast doubt on one or more of the PSG model's assumptions. Conversely, the presence of such invariance would support all of those assumptions, including temporal independence.

\textsuperscript{12}In the top panel of Figure 11, the cumulative distribution of signal-trial reaction times is given by the following expressions: \( F(d) = 0 \) for \( t \leq .3; F(d) = 12.5(t - .3)^2 \) for \( .3 < t \leq .5; F(d) = 12.5[8(t - .3) - (t - .3)^2 - .08] \) for \(.5 < t \leq .7; F(d) = 1 \) for \( t > .7 \). The cumulative distribution of regular-trial reaction times is given by the following expressions: \( F(d) = 0 \) for \( t \leq .45; F(d) = 500(t - .45)^2 \) for \(.45 < t \leq .55; F(d) = 4.8(t - .4) - 8(t - .4)^2 - .36l/36 \) for \(.55 < t \leq .7; F(d) = 1 \) for \( t > .7 \). With these expressions, Equation 2 can be used to calculate the illegitimate (i.e., nonmonotonic) distribution of guessing-completion times, \( F(d) \), represented by the dotted function in the top panel of Figure 11. The corresponding hazard functions in the bottom panel of Figure 11 may be calculated by differentiating the preceding expressions with respect to \( t \) and then applying Equation 5.

\textsuperscript{13}Because the numerators and denominators that define hazard functions are always nonnegative, a legitimate hazard function can never be negative either.

\textsuperscript{14}For example, one possible failure of the temporal-independence assumption is that responses based on completion of the guessing processes might be slowed or suppressed if a subject detects the response signal at a moment when the normal processes have only a short time left before finishing. This could alter both the location and the shape of the derived guessing-completion time distribution as a function of signal lag. Relatively long lags would tend to produce distributions of guessing-completion times with excessively large medians and ranges compared with those produced by shorter lags. Such discrepancies might also arise from failures in which the initiation of the guessing processes terminates the normal processes even though the normal processes have only a short time left before finishing.

\textsuperscript{15}An anonymous reviewer has described this test in terms of "trial independence" and "distributional independence." Trial independence is a theoretical property corresponding to the absence of a trial-by-trial correlation between the underlying durations of the guessing and normal processes, as claimed in the temporal-independence assumption. Distributional independence is an empirical property corresponding to the presence of shape invariance among the estimated distributions derived from Equation 2 for different signal lags. Also, with distributional independence, the lag effects on median guessing-completion times would equal the objective differences between the magnitudes of the signal lags. As argued earlier, distributional independence is implied by a combination of trial independence and other ancillary assumptions (e.g., the winner-takes-all assumption) of the PSG model. Failure to obtain distributional independence would therefore cast doubt on the existence of trial (i.e., temporal) independence. Conversely, trial independence would be supported by obtaining distributional independence in the derived distributions of guessing-completion times. The latter implication follows because there is no other plausible way that distributional independence based on Equation 2 could occur if trial independence does not hold. For example, if the initiation of the guessing processes interferes with the progress of the normal processes, then this would ordinarily preclude distributional independence (cf. Footnote 14).
and winner-takes-all, because there is no other plausible way
Equation 2 could yield invariant guessing-completion time dis-
tributions (cf. Footnote 14).

Full-access assumption. It is more difficult to test the full-access assumption of the PSG model, which provides another part of the basis for speed-accuracy decomposition. The difficulty stems from a case of the proverbial "chicken-and-egg" problem. On the one hand, obtaining valid estimates of accumulated partial information constitutes the primary objective of the model and technique; this is the "chicken" that we are after. On the other hand, to obtain the desired estimates, the model and technique must assume that the guessing processes exploit all available partial information; this is the "egg" from which the "chicken" has to come. If the full-access assumption fails, then the obtained partial-information estimates would be too low. Such estimates do not, however, offer a direct way of discovering whether any additional information was available but went unused.

As a result, only indirect tests of the full-access assumption are feasible. For example, one possibility is that under extreme circumstances the estimated accuracy of the guessing processes might be significantly below chance. This would suggest that the guessing processes fail to use whatever partial information is available from the normal processes and, furthermore, that the guessing processes actually interfere with the accuracy of the normal processes on signal trials. We could then reject the full-access assumption.

A second possibility is that the estimated guessing accuracy might exceed the observed accuracy of responses on regular trials, which supposedly involve the normal processes alone. This would suggest that the guessing processes somehow supercharge the normal processes, thereby enhancing their accuracy on signal trials and creating an impression of overflowing partial information rather than mere full access. Again the full-access assumption could then be rejected.

A third possibility is that the estimated guessing accuracy might fall within acceptable limits (i.e., between the chance level and the accuracy of regular-trial responses), but the guessing-accuracy estimates might oscillate over time, deviating from all patterns predicted by reasonable information-processing models. This would likewise cast doubt on the full-access assumption. Under the PSG model, there are no plausible grounds for explaining such oscillations unless that assumption has failed somehow.

Barring these extreme circumstances, one must proceed on faith that the full-access assumption is innocent until proved guilty of an obvious violation. The assumption of full access may be further justified through extensive applications of speed-accuracy decomposition. To the extent that various plausible patterns of accumulated partial information emerge across different cognitive tasks, including a range of cases like those illustrated previously in Figure 6, then the full-access assumption would stand affirmed.

Implications for Models of Information Processing

Of course, the objective of speed-accuracy decomposition is not merely to test the assumptions of the PSG model. We have developed this technique and metamodel as a way to measure accumulated partial information and pursue the discrete-versus-continuous distinction between substantive information-processing models. Depending on which of the information-accumulation functions in Figure 6 obtains empirically, speed-accuracy decomposition can provide additional grounds for determining what particular type of model should be adopted to interpret reaction time data from given cognitive tasks. The discrete stage model (S. Sternberg, 1969), cascade model (McClelland, 1979), or stochastic diffusion model (Ratcliff, 1978, 1988) might, for example, emerge as a favored candidate. The relations between these alternative models and expected information-accumulation functions are as follows.

Discrete Stage Model

According to a discrete stage model like that of S. Sternberg (1969), partial information should accumulate in a steplike manner over time, if both the internal states and outputs of the component stages are discrete. The accumulation might be all-or-none, or it might exhibit at least one intermediate plateau of partial information. Similar expectations would hold for a less restricted stage model such that (a) partial information within each stage accumulates continuously, but (b) the internal contents of the stages are inaccessible before they have been completed, and (c) their outputs are discrete quantal packets of information. Thus, if we obtained partial-information accumulation functions like those in the top or middle panels of Figure

16 The implications of below-chance guessing accuracy follow from Equation 4. As part of the guessing-accuracy estimates provided by this equation, the observed accuracy of responses on signal trials (i.e., \( P_s(\text{correct}) \) ) is reduced by a term involving the accuracy of the normal processes (i.e., \( P_n(\text{correct}|a < t_w) \) ), which comes from the observed accuracy of responses on regular trials. If the accuracy of the normal processes on signal trials were lower than indicated by the regular-trial response accuracy, then a below-chance estimate of the guessing accuracy could emerge. The normal-process accuracy might be lower on the signal trials than on regular trials because the response signal interferes with the ability of the normal processes to use accumulated information.
In certain special cases, however, a discrete stage model could yield an apparently continuous gradual increase of accumulated partial information. One way for this to happen is that each component stage might accumulate information continuously, and the contents of each stage might always be available upon demand, even though the stages do not ordinarily transmit their outputs until they have finished. This possibility is worth considering on logical grounds but seems less plausible than the preceding ones. If the contents of the stages are freely accessible regardless of how far they have progressed, then little rationale would exist for each stage not transmitting its partial information continuously to other recipient stages (McClelland & Rumelhart, 1981).

A discrete stage model might also produce an apparently continuous increase of accumulated partial information because it has many slightly different internal states and outputs. If a relatively short time separates the transition from one of these states to the next, and if the transition times vary randomly, then speed-accuracy decomposition would not necessarily reveal them clearly. Some smearing may occur in the partial-information accumulation functions obtained with the decomposition technique, just as we discussed previously regarding standard speed-accuracy trade-off methodology (Figure 5). There is no guaranteed way to avoid this, so as in the past, it may still be difficult to discriminate empirically between discrete and continuous models under some circumstances. However, the difficulty seems less severe here. If smearing results from a mixture of many similar discrete states and short transition times, then a continuous model would, in essence, provide a very close approximation to actual reality (cf. Meyer, Yantis, Osman, & Smith, 1985).

Cascade Model

According to the cascade model (McClelland, 1979), the performance of cognitive tasks involves a continuous deterministic flow of activation through a system of temporally concurrent component processes. The activation builds gradually in each component (Footnote 2) until it crosses a set threshold in a final response-execution process, triggering an overt physical movement. Consequently, a smooth increasing partial-information accumulation function should emerge from this model, analogous to the form of typical speed-accuracy trade-off curves. As time passes, there should be more and more intermediate activation available for taking action in response to a peremptory signal before the final activation threshold has been reached. Thus, if a pattern of accumulated partial information like the one in the bottom panel of Figure 6 were obtained, it would add credibility to the cascade model. Without significant embellishment, there is no obvious way the cascade model could account for step functions like those in the top and middle panels of Figure 6.

Stochastic Diffusion Model

The accumulation of partial information under the stochastic diffusion model depends on special assumptions made about the drift of response strength associated with processing a test stimulus. In Ratcliff's (1978, 1988) formulation of the model, response-strength drift is assumed to entail Brownian motion governed by a Wiener (i.e., Gaussian) random process (cf. Cox & Miller, 1965) with an adjustable rate parameter. This assumption endows the model with considerable freedom for predicting the forms of partial-information accumulation functions obtained through speed-accuracy decomposition.

Ratcliff (1988) has shown that if the drift-rate parameter remains constant across trials, then for the guessing processes on signal trials, the stochastic diffusion model yields a negatively accelerated accumulation of partial information. According to the model, this information quickly approaches asymptote at an intermediate level relative to the accuracy of responses on regular trials. The obtained partial-information accumulation function would then approximate a single step up to an intermediate plateau, much like one also expects under discrete stage models that produce a single quantum of partial information before being completed (cf. Figure 6, middle panel). It is also possible for the stochastic diffusion model to produce partial information that first increases and then decreases over time during signal trials of the TRT procedure (Ratcliff, 1988). A partial-information accumulation function shaped like an inverted U would result if the rate parameter of the drift process, not just the individual upward and downward movements of response strength, varies randomly from trial to trial. For an explanation of these somewhat counterintuitive predictions, see Ratcliff (1988).

We should stress that not all models based on stochastic information accumulation have the same characteristics. Their characteristics may vary systematically as a function of specific assumptions made about the random mechanisms and decision rules involved in accumulating and assessing partial information. Some members of this broad class predict continuous increases of partial information over time, not an intermediate plateau or a downward trend from an intermediate maximum (Ratcliff, 1988). So with respect to the domain of stochastic processing models, speed-accuracy decomposition can yield useful insights about which particular cases offer the best bets for interpreting reaction time data and other related results.

Summary

A summary of the most plausible correspondences between various models of information processing and patterns of accumulated partial information appears in Table 1. The table deals with the discrete stage model (S. Sternberg, 1969), cascade model (McClelland, 1979), and stochastic diffusion model (Ratcliff, 1978, 1988), as well as some other well-known cases (e.g., McClelland & Rumelhart, 1981; J. Miller, 1982a; Morton, 1969). For each case, the expected partial-information accumulation functions are indicated by the starred cells. These functions include several of the ones outlined previously (Figure 6),

17 Although the cascade model assumes that the flow of activation between processes is deterministic, stochastic variability of reaction times may occur under the model because of random fluctuations in the threshold or base level of activation (Ashby, 1982; Meyer, Yantis, Osman, & Smith, 1985).
Partial-Information Accumulation Functions Expected Under Alternative Discrete and Continuous Information-Processing Models

<table>
<thead>
<tr>
<th>Model</th>
<th>Reference</th>
<th>Chance guessing</th>
<th>Quasi step-function (single plateau)</th>
<th>Quasi step-function (multiple plateaus)</th>
<th>Monotone increasing function</th>
<th>Continuous inverted-U function</th>
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</thead>
<tbody>
<tr>
<td>Discrete stages</td>
<td>S. Sternberg (1969)</td>
<td>*</td>
<td>*</td>
<td>*</td>
<td>*</td>
<td>*</td>
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<tr>
<td>Cascade</td>
<td>McClelland (1979)</td>
<td>*</td>
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<tr>
<td>Stochastic diffusion</td>
<td>Ratcliff (1978)</td>
<td>*</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Asynchronous discrete coding</td>
<td>J. Miller (1982a)</td>
<td>*</td>
<td>*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Logogen</td>
<td>Morton (1969)</td>
<td>*</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Interactive activation</td>
<td>McClelland &amp; Rumelhart (1981)</td>
<td>*</td>
<td></td>
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<td></td>
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<tr>
<td>Random walk</td>
<td>Ratcliff (1988)</td>
<td>*</td>
<td>*</td>
<td></td>
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<td></td>
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<tr>
<td>Stochastic runs</td>
<td>Audley (1960)</td>
<td>*</td>
<td>*</td>
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<td>*</td>
</tr>
<tr>
<td>Dual counter</td>
<td>Pike (1973)</td>
<td>*</td>
<td>*</td>
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</tbody>
</table>

Note. Starred cells indicate possible predictions by each model. For further discussion of the runs and counter models, see Ratcliff (1988).

Application to Studies of Word Recognition

The distinction between discrete and continuous mental processes is important for understanding how subjects perform tasks in various cognitive domains, such as ones involving visual imagery, selective attention, word recognition, sentence comprehension, reasoning, and problem solving. For each of these domains, some theorists have proposed that knowledge is represented in a continuous analog format or that knowledge structures are processed through continuous operations with gradual outputs of partial information (e.g., Cooper & Shepard, 1973; DeSoto, London, & Handel, 1965; Kosslyn, 1980; McClelland, 1979; McClelland & Rumelhart, 1981; McCloskey & Glucksberg, 1979; Morton, 1969; Shepard & Metzler, 1971; E. E. Smith et al., 1974). Other theorists have proposed instead that knowledge is represented in a discrete propositional format or that knowledge structures are processed through discrete operations with quantized outputs of information (e.g., J. R. Anderson, 1976; Clark, 1969; Clark & Chase, 1972; Just & Carpenter, 1976; Meyer, 1970, 1975; Meyer et al., 1974, 1975; Rubenstein et al., 1971; R. J. Sternberg, 1977). Resolution of these controversies would shed needed light on the formats of underlying knowledge structures and on the processes responsible for exploiting their content. It would also help to determine what methodologies are most appropriate for studying different forms of cognition and what models are most valid for interpreting results obtained through those methodologies.

An especially appropriate domain in which to pursue the discrete-versus-continuous distinction concerns the structures and processes that mediate word recognition. Word recognition has been a major topic of investigation since the dawn of experimental cognitive psychology (Cattell, 1886; Woodworth, 1938). As part of this investigation, criticisms of conventional reaction time procedures and of inferences drawn from them have arisen repeatedly (e.g., Corbett & Wickelgren, 1978; McClelland, 1979; Wickelgren, 1977). Consequently, there is already a rich body of theoretical and empirical wisdom regarding word recognition that could guide the present development of speed-accuracy decomposition. The study of word recognition may also be relevant to other aspects of cognition such as perception, memory retrieval, and sentence comprehension. If we could successfully apply the decomposition technique in this domain, it would set the stage for extending our approach to a variety of other related areas.

To characterize the nature of word recognition, some highly influential models of both the discrete and continuous classes have been proposed. These competing word-recognition models hypothesize specific mechanisms by which a person might go from the visual and auditory manifestations of words to their associated graphemic, phonemic, syntactic, and semantic content. The alternatives are illustrated nicely in terms of two examples, one formulated by Rubenstein et al. (1971) and the other by McClelland and Rumelhart (1981).

Rubenstein et al. (1971) formulated a discrete model of word recognition that is based on two major stages with quantized all-or-none outputs. Their model is intended to describe the recognition of printed words. Its first major stage entails transforming a printed word into a phonemic code via general

\*\*\* We use the term quasi step-function for cases in which the corners of true step functions may appear a bit rounded because of random variability in either the times of transition between discrete information states or the stochastic drift of response strength.
grapheme–phoneme correspondence rules and then using the derived phonemic code to access the word’s storage location in a mental lexicon. The second major stage entails a spelling check that verifies whether the content of the accessed location, including information about graphemic composition, agrees with the word’s original orthography (i.e., spelling). This verification process is needed to deal with words (e.g., "blew") and nonwords (e.g., "bloo") whose pronunciations sound like those of other words (e.g., "blue") but whose spellings differ from them. Without the spelling check, the recognition process could end up at the wrong storage location for a given word and never be corrected appropriately. A combination of the two stages (i.e., phonemic access plus spelling check) accounts neatly for several empirical results obtained by Rubenstein et al. (1971), such as the observations that homophonic words (e.g., "blue" and "blew") take longer to recognize on the average than do nonhomophonic words (e.g., "green") and that homophonic nonwords (e.g., "bloo") take longer to reject than do nonhomophonic nonwords (e.g., "ploo"). Discrete multistage models of word recognition have also been entertained by a number of other theorists (e.g., Atkinson & Juola, 1973; Becker, 1980; Meyer & Ruddy, 1973; Meyer et al., 1974, 1975).

In contrast, McClelland and Rumelhart (1981) formulated a word-recognition model whose component processes operate concurrently on information at several different levels of abstraction and whose outputs (i.e., spreading activation) pass continuously back and forth between levels, rather than progressing in a discrete stagelike fashion. A concerted effort has been made to justify this alternative conceptualization of the recognition process. The interactive-activation model of word recognition explains a variety of experimental data, including the so-called word-superiority effect (Reicher, 1969) and the pseudoword advantage (Baron & Thurston, 1973) found in subjects' reports of target letters from tachistoscopically presented letter strings. For example, the word-superiority effect, which involves higher accuracy identification of letters in real words than of isolated letters or letters in nonwords, fits especially well with the model because activation that reaches the lexical level may flow continuously back downward to support information processing at the lower graphemic level (McClelland & Rumelhart, 1981). It therefore seems worth seriously entertaining such continuous models as alternatives to discrete ones for word recognition. However, more work is still required before a definitive choice can be made.

Given these considerations, we have opted to demonstrate the speed–accuracy decomposition technique by applying it in several studies of visual word recognition. As outlined already, the domain of word recognition provides a natural testing ground on which the merits of our approach may be evaluated for discriminating discrete versus continuous processing states and outputs. If the application is successful here, it may have implications regarding not only the status of general reaction time models like those discussed earlier (e.g., discrete stage model, S. Sternberg, 1969; cascade model, McClelland, 1979; stochastic diffusion model, Ratcliff, 1978) but also the status of important special cases (e.g., discrete verification model, Rubenstein et al., 1971; interactive-activation model, McClelland & Rumelhart, 1981).

**Lexical-Decision Task**

The experiments reported here incorporated a lexical-decision task for studying visual word recognition. In this task, subjects have to decide whether various strings of letters (e.g., "blue" and "ploo") are words or nonwords. Assuming that the nonwords have spellings and pronunciations similar to those of real words, such decisions presumably rely on mental structures and processes such as those hypothesized under the word-recognition models of Rubenstein et al. (1971), McClelland and Rumelhart (1981) and other cognitive theorists (e.g., Becker, 1980; Meyer & Schvaneveldt, 1976; Morton, 1969; Neely, 1976). The lexical-decision task, along with other complementary tasks (e.g., word naming; Meyer et al., 1975), thus offers a convenient way to examine the nature of word recognition.

We have used the speed–accuracy decomposition technique in combination with two versions of the lexical-decision task. In one version, the mapping between test stimuli (i.e., words and nonwords) and correct responses (i.e., positive and negative keypresses) is straightforward. The stimuli are single strings of letters; subjects have to respond "yes" by pressing a positive-response key when the letter string is a word, or "no" by pressing a negative-response key when the string is a nonword. This simple stimulus–response assignment requires encoding just one item (i.e., letter string), accessing the mental lexicon for information about it, making one binary (yes–no) decision on the basis of the outcome of the access operation, and then executing the corresponding response. Because of the assignment's simplicity and directness, subjects can perform the single-string lexical-decision task with relatively high speed and accuracy, producing mean reaction times of 500 ms or less and accuracy levels of 95% or greater (e.g., see Meyer et al., 1975; Rubenstein et al., 1971).

By contrast, the second version of the lexical-decision task used here is somewhat more difficult. It follows previous work by Meyer and Schvaneveldt (1971, Experiment 2). The test stimuli consist of two letter strings in combination, which include word–word (WW), word–nonword (WN), nonword–word (NW), and nonword–nonword (NN) pairs. Subjects have to respond "yes" for both the WW and NN stimuli, indicating that the lexical status of the letter strings is the same. The correct responses for both the WN and NW stimuli are "no," indicating that the lexical status of the letter strings is different. This more complex stimulus–response assignment requires encoding two distinct items, accessing the mental lexicon for information about each of them, making two binary (yes–no) decisions on the basis of that information, comparing the outcomes of these decisions to determine whether they match, and then executing a correct response. Because of such complexity, performance in the dual-string lexical-decision task may yield reaction times well over 500 ms and accuracy levels less than 95% (Meyer & Schvaneveldt, 1971). The increased difficulty presumably results from the extra same–different comparison operation that mediates the overall decision process as well as from the additional encoding and retrieval operations needed to process the multiple letter strings.

Several considerations motivated our adoption of these two versions of the lexical-decision task. On the one hand, it seems likely that the single-string lexical-decision task might offer a
good opportunity for demonstrating how the speed-accuracy decomposition technique can reveal the occurrence of continuous information processing, as expected under the cascade model (McClelland, 1979), interactive-activation model (McClelland & Rumelhart, 1981), and other related alternatives (e.g., Morton, 1969). If such models rather than a discrete verification model (Meyer et al., 1974, 1975; Rubenstein et al., 1971) are correct, then a monotonically increasing accumulation of partial information should emerge when the decomposition technique is applied to data regarding lexical decisions made under the TRT procedure. On the other hand, it seems likely that the dual-string (i.e., same-different) lexical-decision task might offer a good opportunity to reveal the occurrence of discrete information processing. As argued earlier, dual-string lexical decisions may include a comparison process whose inputs are positive or negative lexical-status values and whose output is a positive or negative match (i.e., same vs. different). So the comparison process might easily be discrete, because of the binary nature of the information on which it operates. This prospective discreteness could yield either a constant chance level of guessing accuracy after speed-accuracy decomposition (Figure 6, top panel) or a partial-information accumulation function with at least one intermediate plateau (Figure 6, middle panel), rather than a steadily increasing function (cf. Figure 6, bottom panel). Thus, by comparing subjects’ performance on different versions of the lexical-decision task, the potential of speed-accuracy decomposition for discovering different patterns of partial information may be realized.

There are also additional technical reasons for using the dual-string lexical-decision task as part of our application. Because this task yields relatively long reaction times with high variances (Meyer & Schvaneveldt, 1971), it facilitates optimal temporal placement of response signals on the signal trials. Furthermore, the dual-string lexical-decision task lets us carefully examine certain changes in subjects’ response biases over time. This possibility is enhanced by including two types of positive test stimuli (i.e., WW and NN) and two types of negative test stimuli (i.e., WN and NW).

**Overview of Experiments**

This article reports five experiments involving the lexical-decision task and TRT procedure with mixed regular and signal trials. In Experiments 1 through 4, the dual-string (i.e., same–different) lexical-decision task was used. The objectives of these experiments were to illustrate the speed–accuracy decomposition technique, to validate the assumptions of the PSG model, and to measure the accumulation of partial information for a combination of “normal” word-recognition and lexical-status comparison processes. To achieve these objectives, the lags (SOAs) of the response signals on the signal trials were systematically manipulated, yielding a detailed picture of how partial information is accumulated as a function of time during various phases of word recognition. We anticipated that this manipulation might reveal an intermediate plateau of partial information consistent with a discrete stage model. For purposes of comparison, Experiment 5 used the single-string (i.e., yes–no) lexical-decision task. This lets us check the sensitivity of speed-accuracy decomposition to potentially different patterns of accumulated partial information. Because of the more direct stimulus–response assignment in the fifth experiment, we anticipated that an increasing monotonic accumulation function might emerge there, unlike for the first four experiments in which the stimulus–response assignment was less direct.

**Experiment 1**

The specific aim of Experiment 1 was to determine if and when normal mental processes associated with performing the dual-string lexical-decision task produce useful partial information before completing their set activities. Response signals with two different signal lags were presented on the signal trials. One signal had a relatively short lag, and the other had a long lag compared with those included during subsequent studies (cf. Experiments 2 through 4). Given the reaction times and error rates for these lags, together with results from regular (nonsignal) trials, we measured the amounts of partial information available at two different moments after the onset of the test stimuli.

The lengths chosen for the short and long signal lags stemmed from several empirical and theoretical considerations. On the basis of preliminary pilot data (Meyer & Irwin, 1981), it seemed likely that the shortest completion time (minimum reaction time) achieved by the normal processes of word recognition and lexical-status comparison on regular trials might constitute a major landmark with respect to partial-information accumulation. We suspected that if a response signal induced guesses whose completion times were less than the minimum regular-trial reaction time, then the accuracy of the guessing processes would not exceed a chance level, even though the response signal occurred substantially later than the onset of the test stimulus. This led us to choose a short signal lag for which the resultant guessing processes had completion times just a little less than those of the fastest normal processes. Consequently, the response signal with the short lag may reveal exactly how far the normal processes progress before they start providing useful partial information to the guessing processes. To complement the short signal lag, the other response signal in Experiment 1 had a long lag that induced guesses whose completion times were sometimes greater and sometimes less than those of the normal processes. This lets us check for better-than-chance guessing accuracy at a subsequent moment when the normal processes had perhaps begun producing useful partial information. Experiment 1 therefore offers an initial test of whether performance in the dual-string lexical-decision task involves a single all-or-none output of information (e.g., Figure 6, top panel) or multiple outputs with at least one intermediate level of partial information (e.g., Figure 6, middle and bottom panels).

In addition, Experiment 1 provided initial tests of the PSG model on which speed-accuracy decomposition relies. The model’s temporal-independence assumption implies that varying the response-signal lag should change the median guessing-completion time by the same amount as the lag changes, but that the distributions of guessing-completion times should remain unaffected in other respects (e.g., they ought to have identical shapes regardless of signal lag; Figure 12). If the PSG model is valid, we would likewise expect that the guessing-com-
completion times should be unaffected by manipulations of the WW, NN, WN, and NW stimuli, even though the durations of normal recognition and comparison processes are affected by them. These predictions may be tested by estimating and comparing the guessing-completion times obtained through Equation 2 as a function of signal lag and stimulus type.

Method

Subjects. Four students at the University of Michigan served as paid subjects. They were sampled from a pool of volunteer subjects at the Human Performance Center. Three subjects (J.K., V.S., and S.D.) were male and one (B.F.) was female. All were right-handed native speakers of English who had no apparent visual or motor defects. Each subject participated in a series of hour-long experimental sessions. An average payment of about $4 per session, including a $1.75 salary and a bonus for good performance, was made to each subject.

Apparatus. Subjects, who were tested individually, sat at a table in a moderately illuminated sound-attenuating booth. A digital computer (DEC PDP-11/60) controlled the collection and analysis of data. Attached to the computer was a video terminal (DEC VT-52) that presented the warning signals, test stimuli, response signals, and feedback for the experiment. The terminal's display screen was positioned on the table at a viewing distance of about 0.5 m. Positive responses were made by pressing the "/" key on the terminal's keyboard, and negative responses were made by pressing the "z" key.

Stimuli. To generate the test stimuli, we sampled 256 words from the frequency norms of Kučera and Francis (1967), and we constructed 256 orthographically regular, pronounceable nonwords. All of the words and nonwords contained four letters. Half of the words were common (median frequency = 107 occurrences per million; range = 32 to 3618 occurrences per million), and the other half were rare (median frequency = 2 occurrences per million; range = 1 to 5 per million). This variation yielded a reasonably wide spread in the observed reaction time distributions, facilitating placement of the response signals at desired temporal positions on the signal trials.

The words and nonwords were used to create four types of test stimuli: WW, NN, WN, and NW pairs. The WW and NN stimuli required positive (same) responses, whereas the WN and NW stimuli required negative (different) responses. Half of the stimuli contained both high-frequency words, and the other half contained both low-frequency words. Similarly, half of the WN stimuli and half of the NW stimuli contained high-frequency words, whereas the other half contained low-frequency words. Given this constraint, the assignment of the words and nonwords to the various stimulus types was randomized. New assignments were made for each subject during each session. All four test-stimulus types occurred equally often across the regular trials and across the signal trials.

The words and nonwords appeared on the display screen in uppercase letters. Each letter subtended about 0.35° of visual angle in width and 0.5° in height at a viewing distance of 0.5 m. The two letter strings (words and/or nonwords) of each test stimulus were displayed with one string directly below the other in the middle of the screen, thus subtending overall visual angles of about 1.4° horizontally and 1.1° vertically.

The response signals for the signal trials were auditory buzzes generated with the "bell" character of the video terminal.

Design. The experiment included 10 sessions per subject conducted over a span of 2 to 3 weeks. Sessions 1 through 6 served as practice, and Sessions 7 through 10 provided the data reported here. Each session lasted approximately 1 hr and included 4 trial blocks with 80 trials per block.

During the first two practice sessions, subjects worked exclusively on regular trials. No response signals were presented at part of these trials. The four types of test stimuli (i.e., WW, NN, WN, and NW) occurred equally often per block. This allowed the subjects to master the lexical-decision task before being confronted with the greater demands of the TRT procedure.

During the next four practice sessions, we introduced subjects to the random combination of signal and regular trials. On each trial block of these sessions, there were 32 regular trials, 24 signal trials with short signal lags, and 24 signal trials with long signal lags. The different trial types occurred in a random order, so that subjects could not accurately predict whether a response signal would be presented in conjunction with a given test stimulus. A counterbalanced design was used to assign the various stimulus types to the two different trial types; WW, NN, WN, and NW stimuli were equally frequent on both the regular and the signal trials. Extensive practice was given in order to familiarize subjects fully with the mixture of regular and signal trials. This helped ensure that the complementary tasks of making lexical decisions and detecting response signals did not interfere much, if at all, with each other (cf. Hirst et al., 1980).

The design during the final four test sessions was identical to that of the previous four practice sessions with the TRT procedure. By this time, performance had stabilized reasonably well, and subjects did not experience major conflict in sharing their processing capacity between the lexical-decision and signal-detection tasks. For each subject, the test sessions yielded overall totals of 128 regular trials, 96 short-lag signal trials, and 96 long-lag signal trials involving each type of test stimulus.

Procedure. The procedure implemented the sequences of events outlined in Figure 7 for the regular and signal trials. At the start of each regular trial, a warning signal composed of four dashes arrayed horizontally was presented in the center of the display screen to indicate where the test stimulus would appear. After 0.5 s, the dashes were removed, and a test stimulus composed of two letter strings appeared directly below the dash locations, with one string beneath the other. The subject was supposed to make a positive response if the two strings of letters had the same lexical status (i.e., both words or both nonwords) and a negative response otherwise. We measured the reaction time from the onset of the test stimulus until the response occurred. The subject was instructed to respond as quickly as possible without committing excessive (more than 10%) errors. Following the subject's response, the message "Error" appeared for 0.5 s whenever an incorrect response occurred. No message was presented after a correct response. A blank interval of 1 s separated each trial from the next.

The signal trials, which were mixed randomly with the regular trials, began with a warning signal (horizontal dashes) followed by a test stimulus, just as the regular trials did. The subject was again supposed to aim toward reacting as soon as possible while taking enough time to make a correct response to the test stimulus. However, at some moment after the test stimulus appeared on a signal trial, a response signal was presented. If the subject had not responded already, then upon detecting the response signal, the subject had to react immediately, making his or her best guess about what the correct response was. We encouraged the subject to make an accurate guess that was based on partial information accumulated from processing the test stimulus up to the moment when the response signal was detected. It was also emphasized that action should take place immediately after the response signal. Reaction time was measured from the onset of the test stimulus until the response occurred. At the end of each signal trial, the subject received feedback about the accuracy of the response, as on the regular trials. In addition, feedback was provided about the latencies of responses relative to the onset of the response signal. When a response occurred before the signal onset or within 300 ms after it, the message "Good Time" appeared on the display screen; otherwise, the message "Too Slow" was displayed.

Because the subjects could not predict beforehand whether a response signal would be presented on a particular trial, it behooved them to approach every trial as if it were going to be a regular (nonsignal) trial, with the proviso that they should be prepared to react immediately
without further deliberation if a peremptory response signal was subse-
quently detected. On some signal trials, subjects responded before the
response signal was presented, and they were instructed simply to ig-
nore the signal in such cases. Our instructions, together with the ran-
dom mixture of regular and signal trials, therefore encouraged the "nor-
mal" processes for the regular trials to be used as well on the signal
trials.

At the end of each trial block, subjects received detailed feedback
about their performance over the whole block. They were shown the
number of correct responses, the number of incorrect responses, and
the mean reaction time for the block. In addition, a net point score was
displayed. The point score came from a combination of regular-trial
and signal-trial performance measures. On regular trials, a subject
earned 100 points for each correct response, lost 50 points for each
incorrect response, and lost 30 points for every 100 ms in mean reaction
time. On signal trials, the subject earned 120 points if a correct response
occurred before or soon enough after the response signal (i.e., no later
than 300 ms following its onset). The subject lost 600 points if the re-
sponse to the signal was too slow, regardless of whether the response was
correct or incorrect. No points were awarded or deducted for suffi-
ciently fast but incorrect responses. The point score provided an objec-
tive summary of the subject's performance. It was also used as the basis
for a bonus paid to the subject. The bonus included $1 per every 100
points earned during the experiment.

Response-signal lags. Experiment 1 included response signals with
two different signal lags (SOAs). The lag was either short or long. The
short lag was designed to induce guessing processes whose completion
times, as estimated through Equation 2, were always slightly less than
those of the fastest normal processes. In contrast, the long lag was de-
signed to induce guessing processes that sometimes finished before and
sometimes finished after the normal processes did. Obtaining these ob-
jectives required adjusting the response-signal lags relative to the distri-
butions of reaction times on regular (nonsignal) trials, which presum-
ably reflect the completion times of the normal recognition and compar-
ison processes associated with performing the dual-string lexical-
decision task.

We adjusted the response-signal lags by using a staircase tracking al-
gorithm (cf. Meyer et al., 1984; Meyer, Yantis, Osman, & Smith, 1985).
The algorithm was applied for each subject individually throughout all
test sessions. It incorporated a simple up-and-down rule (Levitt, 1971) that
tracked the median reaction times of responses to WW test stimuli on
regular trials during each trial block. Whenever a WW stimulus yielded
a reaction time exceeding the current estimated value of the median, the
estimate was increased by 10 ms; the estimate was de-
creased by 10 ms whenever a WW stimulus yielded a reaction time less
than this value. These adjustments let us take account of individual
differences in subjects' speed of normal information processing, so the
signal lags could be tailored to each subject. They also permitted drifts
in subjects' performance across trial blocks and sessions to be accom-
modated systematically.

Following each trial block for each subject, the estimated median re-
action time of responses to WW stimuli on prior regular trials deter-
ned the long signal lag for the next block. In particular, the long lag
was set to equal the median WW reaction time estimate minus an aver-
age value of 200 ms, which depended on the mean duration of the sub-
jects' guessing processes. The adjustment resulted in a long signal lag
whose value averaged approximately 510 ms across subjects and ses-
sions, measured from the onset of the test stimuli. On signal trials in
which the response signal with the long lag was presented, it induced
guessing processes that finished ahead of the normal processes roughly
50% of the time for WW test stimuli.

We positioned the response signal with the short lag such that the
guessing processes induced by it always finished before the normal pro-
cesses, but such that the median guessing-completion time was only 50
ms or so less than the completion times of the fastest normal processes.
This involved examining each subject's minimum reaction times for
WW stimuli on the regular trials, which produced the fastest normal
processes. An average value of 230 ms was subtracted from these min-
ima, yielding a mean value of about 260 ms for the short signal lag.

Data analyses. We performed several different types of analyses on
the data from the regular and signal trials. Some of these involved analy-
sest of variance in which the response-signal lags (i.e., short and long)
and types of test stimuli (i.e., WW, NN, WN, and NW) were treated as
fixed effects, and subjects were treated as a random effect. This allowed
us to demonstrate the reliability of our results across subjects. Other
analyses involved Monte Carlo simulations based on bootstrap methods
(Diaconis & Efron, 1983; Efron, 1979) in which the reliability of certain
results was tested for each subject individually against predictions de-
ived from the PSG model.

Results

The results of Experiment 1 include several related measures. First,
there are the reaction times and error rates obtained on the
regular trials, which reflect the effects of stimulus type (i.e.,
WW, NN, WN, and NW) on the duration and accuracy of nor-
mal recognition and comparison processes in the dual-string lexical-decision
task. These need to be considered in detail be-
cause they provide part of the basis for applying the speed-accu-
ricacy decomposition technique, for testing the assumptions of
the PSG model (Figures 10 and 12), and for assessing the accu-
mulation of partial information. For example, to the extent that
the various types of test stimuli differentially affect the regular-
trial reaction times but not the subsequent derived estimates of
guessing-completion times, this would support the temporal-
dependence assumption of the PSG model on which the de-
composition technique rests.

Second, there are the reaction times and error rates obtained
on the signal trials. According to the PSG model, data from the
signal trials embody a mixture of contributions from the as-
sumed normal and guessing processes. These data need to be
considered because they provide another part of the basis for
applying the decomposition technique and for making infer-
ences about the nature of the guessing processes. By combining
various signal-trial data with regular-trial data in Equations 2
and 4, we may estimate both the guessing-completion time dis-
tributions and the amount of partial information available to
the guessing processes from the normal processes at selected
moments in time after the onset of the test stimuli.

Finally, there are the estimated distributions of guessing-
completion times and partial-information accumulation func-
tions, which constitute the ultimate objective of speed-accu-
ricacy decomposition. These need to be considered in order to
test the PSG model and to assess the forms of output produced
by the normal processes of word recognition and lexical-status
comparison. It is the derived data regarding the guessing pro-
cesses that reveal whether performance involves discrete or con-
tinuous internal states and outputs of information.

In what follows, we consider each aspect of the results, dis-
cussing how they relate to our present theoretical and empirical
concerns.

Regular trials. Some results from the regular trials appear in
Table 2. Here we have included the mean reaction times of cor-
rect responses, the mean reaction times of incorrect responses,
and the accuracy (percentage of correct responses) for each type of test stimulus (WW, NN, WN, and NW). The mean reaction times were obtained by calculating the median latency that each subject produced in response to a given stimulus type and then averaging these medians across subjects. Because relatively few incorrect responses occurred on the regular trials, keep in mind that the mean reaction times associated with the incorrect responses are not as reliable as those associated with the correct responses.

The overall accuracy of responses on the regular trials exceeded 94%. There were no significant differences among the accuracy levels for the various stimulus types, \( F(3, 9) = 1.89, p > .2 \). The uniformly high response accuracy suggests that subjects typically set a high information threshold for completing that the mean reaction time produced in response to a particular stimulus type was less than a constant \( C (0 < C < \infty) \). The functions include the reaction times of both correct and incorrect responses. We obtained them by first collecting individual cumulative distribution functions for each subject and then Vincentizing the results across subjects to form cumulative distribution functions based on the group data. Vincentizing, which involves averaging equivalent quantiles of the individual distribution functions within a set, let us preserve the general shapes of the underlying distributions associated with each subject and stimulus type (Ratcliff, 1979; E. A. C. Thomas & Ross, 1980).

From Figure 13, we see that the differences between the reaction times for the various stimulus types extended throughout the entire time range. For example, the fastest responses to NN stimuli were slower than the fastest responses to WW stimuli, and the slowest responses to WW stimuli were faster than the slowest responses to NN stimuli. This pattern has important implications for subsequent analyses, where we estimate the cumulative distribution functions of completion times for the guessing processes on signal trials, showing that the guessing-completion times were not affected significantly by stimulus type even though the reaction times on regular trials were.

**Long-lag signal trials.** Some results from the signal trials on which the response signal had a long lag appear in Table 2 (bottom rows). Here again we have included the mean reaction times of correct responses, the mean reaction times of incorrect responses, and the response accuracy for each stimulus type. The mean reaction times were calculated by averaging the medians produced by individual subjects in response to a given type of stimulus. Both the normal and guessing processes assumed under the PSG model presumably contributed to these data. Thus, by examining them and making comparisons with

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**Table 2**

**Results From the Regular and Signal Trials of Experiment 1**

<table>
<thead>
<tr>
<th>Trial &amp; stimulus type</th>
<th>Mean reaction time (milliseconds)</th>
<th>Response accuracy (% correct)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Correct responses</td>
<td>Incorrect responses</td>
</tr>
<tr>
<td>Regular</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Word-word</td>
<td>703</td>
<td>830</td>
</tr>
<tr>
<td>Nonword-nonword</td>
<td>867</td>
<td>851</td>
</tr>
<tr>
<td>Word-nonword</td>
<td>806</td>
<td>677</td>
</tr>
<tr>
<td>Nonword-word</td>
<td>792</td>
<td>853</td>
</tr>
<tr>
<td>Signal</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Word-word</td>
<td>464</td>
<td>466</td>
</tr>
<tr>
<td>Nonword-nonword</td>
<td>469</td>
<td>465</td>
</tr>
<tr>
<td>Word-nonword</td>
<td>466</td>
<td>471</td>
</tr>
<tr>
<td>Nonword-word</td>
<td>465</td>
<td>463</td>
</tr>
<tr>
<td>Signal</td>
<td></td>
<td></td>
</tr>
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<td>Word-word</td>
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</tr>
<tr>
<td>Nonword-nonword</td>
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<td>695</td>
</tr>
<tr>
<td>Word-nonword</td>
<td>688</td>
<td>704</td>
</tr>
<tr>
<td>Nonword-word</td>
<td>678</td>
<td>695</td>
</tr>
</tbody>
</table>

*Note:* Signal₁ = short lag; signal₂ = long lag.

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Further details regarding the reaction times for the various types of stimuli on the regular trials appear in the top panel of Figure 13. This panel contains four cumulative distribution functions, each of which represents the probability that an observed reaction time produced in response to a particular stimulus type was less than a constant \( C (0 < C < \infty) \). The functions include the reaction times of both correct and incorrect responses. We obtained them by first collecting individual cumulative distribution functions for each subject and then Vincentizing the results across subjects to form cumulative distribution functions based on the group data. Vincentizing, which involves averaging equivalent quantiles of the individual distribution functions within a set, let us preserve the general shapes of the underlying distributions associated with each subject and stimulus type (Ratcliff, 1979; E. A. C. Thomas & Ross, 1980).

The mean reaction times of correct regular-trial responses exhibited a pattern similar to one reported by Meyer and Schvaneveldt (1971). Positive (same) responses were significantly faster on the average for WW stimuli than for NN stimuli, \( F(1, 9) = 15.9, p < .01 \). Negative (different) responses for WN and WW stimuli had intermediate reaction times that approximately equaled each other, \( F(1, 9) < 1.0, p > .5 \). These data reflect how long the normal recognition and comparison processes took to finish successfully with the various stimulus types. Although the regular trials were mixed randomly with the signal trials, rather than being blocked separately, we found no evidence that regular-trial performance differed qualitatively from what has been observed previously in conventional reaction-time experiments with the dual-string lexical-decision task (cf. Meyer & Schvaneveldt, 1971). The inclusion of frequent response signals did not seem to alter the nature of the normal processes.

For example, incorrect responses might occur because subjects misencode the stimulus words or lack prior experience with them. There might also be incorrect responses because of malfunctions at a peripheral motor level. Regardless of how errors arise on the regular trials, speed-accuracy decomposition still lets one separate the contributions of the normal and guessing processes to performance on the signal trials.

Further details regarding the reaction times for the various types of stimuli on the regular trials appear in the top panel of Figure 13. This panel contains four cumulative distribution functions, each of which represents the probability that an observed reaction time produced in response to a particular stimulus type was less than a constant \( C (0 < C < \infty) \). The functions include the reaction times of both correct and incorrect responses. We obtained them by first collecting individual cumulative distribution functions for each subject and then Vincentizing the results across subjects to form cumulative distribution functions based on the group data. Vincentizing, which involves averaging equivalent quantiles of the individual distribution functions within a set, let us preserve the general shapes of the underlying distributions associated with each subject and stimulus type (Ratcliff, 1979; E. A. C. Thomas & Ross, 1980).

From Figure 13, we see that the differences between the reaction times for the various stimulus types extended throughout the entire time range. For example, the fastest responses to NN stimuli were slower than the fastest responses to WW stimuli, and the slowest responses to WW stimuli were faster than the slowest responses to NN stimuli. This pattern has important implications for subsequent analyses, where we estimate the cumulative distribution functions of completion times for the guessing processes on signal trials, showing that the guessing-completion times were not affected significantly by stimulus type even though the reaction times on regular trials were.
The accuracy of responses on the long-lag signal trials was about 76%, still significantly above chance, $F(1, 3) = 53.6$, $p < .001$, but less than the response accuracy on regular trials, $F(1, 3) = 55.5$, $p < .001$. The long signal lag induced more incorrect responses to some types of test stimuli than to others. For example, the accuracy level was lower on the average in response to NN stimuli than in response to WW stimuli, $F(3, 9) = 6.75$, $p < .02$. These effects may have stemmed from the influence of stimulus type on the durations of the normal processes, which modulate the signal-trial reaction times through the assumed race with the guessing processes. To the extent that the normal processes have longer completion times for difficult stimuli, the race would not be won as quickly on the average, even if the durations of the guessing processes are uncorrelated with stimulus type and with the durations of the normal processes (cf. Figure 13).

Further details regarding the reaction times for the various types of test stimuli on the long-lag signal trials appear in the middle panel of Figure 13. Here we have plotted Vincentized cumulative distributions of reaction times from a combination of all correct and incorrect responses to each stimulus type as a function of signal lag. The right-hand cluster of four distribution functions represents the reaction times associated with response signals that had a long lag.

Several features of these distributions, which reflect the hypothesized race between the normal and guessing processes, should be noted. Because the guessing processes occasionally beat the normal processes, the reaction time distributions found on long-lag signal trials were closer together, steeper, and shifted more toward the lower end of the time scale than were those found on the regular trials (cf. Figure 13, top panel). Nevertheless, there was still some effect of stimulus type. For example, the lower tail of the cumulative distribution obtained with WW stimuli on long-lag signal trials started to rise sooner from the lower end of the time scale and reached its median level more quickly than did the corresponding ones obtained with other test stimuli. This difference occurred even though for long-lag signal trials, all of the distributions reached their asymptotes at about the same time, as expected from the PSG model.

Short-lag signal trials. Some results from the signal trials on which the response signal had a short lag appear in the center rows of Table 2. There were significantly fewer correct responses on short-lag signal trials than on long-lag signal trials, $F(1, 3) = 31.8$, $p < .01$. With a short signal lag, the response accuracy averaged across subjects and stimuli did not significantly exceed a chance level (mean accuracy = 52.2%), $F(1, 3) = 1.5$, $p > .2$. Three of the 4 subjects (i.e., J.K., B.F., and S.D.) had mean response accuracies within 2% or less of chance. The other subject (V.S.) performed slightly farther above chance (mean response accuracy = 56.9%), but this was due almost entirely to his relatively high (87.6%) accuracy in response to the WW stimuli. Such high accuracy did not occur in general across subjects for the WW stimuli. Instead, the individual subjects differed greatly from one another with respect to which stimulus types received the most correct responses on short-lag signal trials. As a result, the average effect of stimulus type on response accuracy, although rather large, was not statistically significant.
Results Regarding the Guessing Processes on Signal Trials in Experiment I

Table 3

<table>
<thead>
<tr>
<th>Trial &amp; stimulus type</th>
<th>Completion time (milliseconds)</th>
<th>Duration (milliseconds)</th>
<th>Interquartile range (milliseconds)</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Signal</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Word–word</td>
<td>445</td>
<td>187</td>
<td>59</td>
<td>49.9</td>
</tr>
<tr>
<td>Nonword–nonword</td>
<td>455</td>
<td>197</td>
<td>55</td>
<td>35.6</td>
</tr>
<tr>
<td>Word–nonword</td>
<td>452</td>
<td>194</td>
<td>55</td>
<td>55.7</td>
</tr>
<tr>
<td>Nonword–word</td>
<td>453</td>
<td>194</td>
<td>55</td>
<td>65.8</td>
</tr>
<tr>
<td>Signal</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Word–word</td>
<td>692</td>
<td>178</td>
<td>58</td>
<td>69.0</td>
</tr>
<tr>
<td>Nonword–nonword</td>
<td>697</td>
<td>183</td>
<td>45</td>
<td>61.2</td>
</tr>
<tr>
<td>Word–nonword</td>
<td>694</td>
<td>180</td>
<td>51</td>
<td>71.4</td>
</tr>
<tr>
<td>Nonword–word</td>
<td>689</td>
<td>175</td>
<td>52</td>
<td>74.3</td>
</tr>
</tbody>
</table>

Note: Signal 1 = short lag; signal 2 = long lag.

$F(3, 9) < 1.0, p > .5$. This lack of significance may be attributed to idiosyncratic variations of response bias in the guessing processes, as discussed later.

The mean reaction times of correct and incorrect responses on short-lag signal trials did not differ much from each other (466 ms vs. 467 ms), $F(1, 3) < 1.0, p > .5$, and they were significantly faster than those on long-lag signal trials: for correct responses, $F(1, 3) = 17.0, p < .01$; for incorrect responses, $F(1, 3) = 16.1, p < .01$. Stimulus type had virtually no effect for either the correct responses, $F(3, 9) < 1.0, p > .5$, or the incorrect responses, $F(3, 9) < 1.0, p > .5$, when the signal lag was short. Presumably, the fast reaction times and absence of stimulus-type effects occurred because the short-lag response signal induced the guessing processes to begin soon enough that they almost always finished before the normal processes did.

Vincentized cumulative distributions of reaction times from the short-lag signal trials appear in Figure 13 (middle panel, left-hand cluster of functions). These distributions had virtually the same shape and location regardless of stimulus type, unlike those from the long-lag signal trials (cf. Figure 13, middle panel, right-hand cluster of distributions). Their variances were generally less, and their slopes were steeper than those obtained with the long signal lag. The differences between the results from the short-lag and long-lag signal trials reflect the nature of the underlying guessing processes.

Guessing-completion times. Given the reaction times observed on the regular and signal trials, one may apply the PSG model to estimate distributions of completion times for the guessing processes when the response signals had short and long lags (Equation 2). These distributions indicate the times at which the guessing processes finished relative to the onset of the test stimuli (i.e., WW, NN, WN, and NW), so we can compare them directly with the completion times of the normal processes as revealed by the regular-trial reaction times. Table 3 summarizes the mean guessing-completion times found for each stimulus type and signal lag by averaging individual median guessing-completion times across subjects.

The guessing-completion times for the long-lag signal trials equaled 693 ms on the average. There were no significant effects of stimulus type on the mean guessing-completion times when the response signal had a long lag, $F(3, 9) < 1.0, p > .5$. A difference of 8 ms or less separated each mean from the others. This outcome supports the PSG model and its assumption of temporal independence between the guessing and normal processes. As expected under the model, the durations of the normal processes and the effects of stimulus type on them did not alter the time course of the guessing processes much, if at all. Nearly perfect temporal independence held even though the stimulus-type effects on the durations of the normal processes, as reflected by the differences among the mean regular-trial reaction times (Table 2, top rows), were substantial.

There were marginally significant effects of stimulus type on the mean guessing-completion times when the response signal had a short lag, $F(3, 9) = 2.91, .05 < p < .1$. These times tended to be less for WW stimuli than for NN, WN, and NW stimuli. However, the magnitudes of the stimulus-type effects were small in absolute terms (i.e., 10 ms or less), and none of them approached those observed during regular trials.

The main effects of signal lag on the mean guessing-completion times are also of considerable interest. When the lag of the response signal was short, the guessing processes were completed within an average of 451 ms after the onset of the test stimuli. This completion time was about 242 ms less than the completion time of the guessing processes during the long-lag signal trials. The amount of difference between the mean guessing-completion times for the short and long signal lags is very close to the mean difference of 250 ms between the objective lengths of the lags, as would be expected if the completion time of the guessing processes varies directly with signal lag and does not depend on the duration of the normal processes.

A more thorough examination of the estimated cumulative distributions of guessing-completion times further supports the temporal-independence assumption. In particular, consider the bottom panel of Figure 13, which shows Vincentized distributions of guessing-completion times as a function of stimulus type and signal lag. The lower left-hand cluster of distributions was derived from Equation 2 with the data obtained on short-lag signal trials, and the lower right-hand cluster of distributions was derived from the data obtained on long-lag signal trials. Here it can be seen that the type of test stimulus had little effect on the guessing-completion times throughout their entire range. Except for the constant shift that it produced in the mean guessing-completion times, the manipulation of signal lag (i.e., short vs. long) likewise had little effect on the distributions of guessing-completion times. For example, this is evident in the interquartile ranges of the various guessing-completion time distributions. As Figure 13 (bottom panel) and Table 3 indicate, these distributions had interquartile ranges whose average value was about 50 ms and whose differences from each other were typically 5 ms or less. No significant differences occurred in the interquartile ranges of the guessing-completion times because of either signal lag, $F(3, 9) < 1.0, p > .5$, or stimulus type, $F(3, 9) = 2.71, .05 < p < .1$. This is consistent with the PSG model's assumption that the rate of progress by the guessing processes does not depend either on the time at which the guessing pro-
cesses start relative to the ensuing normal processes or on the type of test stimulus being evaluated by the normal processes.21

**Guessing durations.** Another complementary way of looking at the guessing processes is in terms of their duration. We define the guessing duration to be the amount of time from the onset of the response signal to the moment when the guessing processes produce an overt response. Mean guessing durations may be estimated by subtracting the response-signal lag (SOA) from the mean guessing-completion times (i.e., times at which the guessing processes finish relative to the onsets of the test stimuli).

Table 3 shows estimates of the mean guessing durations for each signal lag and type of test stimulus. The length of the signal lag (short vs. long) did not affect the guessing durations significantly, $F(1, 3) = 1.35, p > .3$. There were no significant effects of stimulus type either, $F(3, 9) = 1.70, p > .2$. On the average, the guessing processes produced an overt response within about 185 ms after the response signal was presented. This duration, which includes a component for detecting the response signal, plus components for making a same–different lexical-status comparison and for executing a motor response, is similar in magnitude to the smallest values found in elementary choice reaction time experiments (Woodworth, 1938). Thus, we infer that the guessing processes had rapid access to whatever partial information was available from the as yet unfinished normal processes.

**Guessing accuracy.** The amount of available partial information may be assessed by applying Equation 4 from the PSG model. As described earlier, this involves calculations based on the distributions of guessing-completion times, the normal-process completion times (i.e., regular-trial reaction times), the response accuracy on regular trials, and the response accuracy on signal trials. These calculations let us remove the contribution of the completed normal processes from the signal-trial response accuracy, leaving a pure residual estimate of how accurate the guessing processes are. The guessing accuracy presumably reflects the utility of partial information accumulated by the normal processes before they have been completed. A summary of the obtained results appears in Table 3 (last column).

For each signal lag and type of test stimulus, this table shows the estimated percentage of signal trials on which the guessing processes were accurate, given that they finished before the normal processes.

First, let us consider the guessing accuracy for long-lag signal trials. As Table 3 indicates, guesses made in response to the negative (i.e., WN and NW) stimulus when the response signal had a long lag were more accurate on the average than guesses made in response to the positive (i.e., WW and NN) stimuli. However, the effect of stimulus type on the guessing accuracy did not reach a statistically significant level because of individual differences in response bias that will be discussed later, $F(3, 9) < 1.0, p > .5$.

Despite these individual differences, we did find some interesting consistencies in the guessing accuracies across all 4 subjects. The mean accuracy of the subjects’ guesses, averaged over the various stimulus types, exceeded chance (50%) by a considerable amount on the long-lag signal trials, $F(1, 3) = 27.4, p < .001$. For J.K., B.F., V.S., and S.D., respectively, the mean guessing accuracies were 67.9%, 64.1%, 64.7%, and 79.8%. Monte Carlo simulations of the PSG model through bootstrap methods (Diaconis & Efron, 1983; Efron, 1979), treating each subject separately (cf. Footnote 21), revealed that this degree of accuracy was unlikely if the guessing processes had no useful partial information on which to base their outputs ($p < .05$ in each subject’s case). The better-than-chance but less-than-perfect accuracy of the guessing processes disconfirms a discrete all-or-none account of performance for the dual-string lexical-decision task.

Next consider the estimated guessing accuracies on signal trials with short signal lags, which appear in Table 3 (top rows, right column) as a function of stimulus type. Averaging these estimates across the various types of test stimuli, we found that the mean accuracy achieved by the guessing processes on short-lag signal trials was only 51.6%, not significantly better than chance, $F(1, 3) = 1.28, p > .4$. The absence of better-than-chance guesses indicates that the short signal lag did not allow the normal processes enough time to accumulate much, if any, useful partial information about whether the members of a stimulus pair had the same lexical status. Some test stimuli (i.e., the WN and NW stimuli) tended to yield more accurate guesses than did others (i.e., the WW and NN stimuli), but the main effects of stimulus type on guessing accuracy when the response signal had a short lag were not reliable, $F(3, 9) < 1.0, p > .5$, because marked individual differences occurred in response bias.

**Guessing sensitivity and bias.** Another way of looking at the accuracy of the guessing processes is in terms of an analysis based on signal-detection theory (Green & Swets, 1966). Although this analysis is not essential for applying the speed–accuracy decomposition technique, it may provide some further insights regarding the accumulation of partial information. If one accepts the additional assumptions of signal-detection theory, one can derive separate sensitivity ($d'$) and bias ($\log \beta$) measures

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21 The temporal-independence assumption is also supported by some distributional analyses that we performed on an individual, subject-by-subject, basis. These analyses involved pairwise comparisons of cumulative distribution functions for the guessing-completion times obtained in response to the WW, NN, WN, and NW stimuli, respectively, on short-lag and long-lag signal trials. There were eight comparisons per subject, including WW versus WN, WW versus NW, NN versus WN, and NN versus NW stimuli at each signal lag. In each comparison, a quasi-chi-square statistic was computed to assess the discrepancy between the distributions of guessing-completion times associated with different types of stimuli. The statistical significance of the results could not be evaluated in conventional terms (e.g., through standard chi-square tables), because the trial-by-trial completion times of the guessing processes were not available as separate raw observations. Thus, we did the evaluation instead through a Monte Carlo simulation, using bootstrap methods developed for conditions in which conventional statistical assumptions do not apply (Diaconis & Efron, 1983; Efron, 1979). As part of the simulation, tables of quasi-chi-square values were derived on the assumption that the PSG model actually holds under our conditions. The resultant tables provided benchmarks to interpret the quasi-chi-square statistics obtained from comparing each subject's estimated distributions of guessing-completion times as a function of stimulus type. A large majority of the comparisons produced values whose magnitudes were not statistically significant ($p > .05$) on the basis of the simulation. Again, this is what we would expect if the temporal-independence assumption of the PSG model is valid at least a first approximation.
Processes in Experiment 1

Signal-Detection Analysis of the Guessing and Normal Processes

The boldfaced rows exclude guesses made in response to word-guesses on long-lag signal trials. The log \( \beta \) measure represents a pure measure of the sensitivity in stimulus discriminations achieved by the guessing processes through partial information from the unfinished normal processes.\(^{22} \) The log \( \beta \) measure represents a pure estimate of response bias that depends on idiosyncratic preferences implicit in the guessing processes.\(^{23} \)

The middle rows of Table 4 show the results of a signal-detection analysis applied to the guessing processes on long-lag signal trials of Experiment 1 (cf. Table 3). For each subject, we calculated a \( d' \) measure of guessing sensitivity based on two component variables: the hit rate (conditional probability of correct guesses) achieved by the guessing processes in response to positive test stimuli (i.e., WW and NN), and the false-alarm rate (conditional probability of incorrect guesses) suffered by the guessing processes in response to negative test stimuli (i.e., WN and NW). The guessing sensitivities of all subjects were considerably greater than zero (mean \( d' = 1.08 \)) when the response signal had a long lag, \( F(1, 3) = 15.0, p < .05 \), confirming the availability of useful partial information that allowed the guessing processes to discriminate the test stimuli at a better-than-chance level. Accompanying this pattern, there were marked variations in the response bias (log \( \beta \)) exhibited by the guessing processes on long-lag signal trials. Two subjects (V.S. and B.F.) had values of log \( \beta \) less than zero, tending to make more positive than negative responses while guessing. The other two subjects (J.K. and S.D.) had values of log \( \beta \) greater than zero, tending to make more negative than positive responses while guessing.

The top rows of Table 4 show the corresponding results of a signal-detection analysis applied to the guessing processes on short-lag signal trials. Presenting a response signal after a relatively short lag decreased both guessing sensitivity and response bias on the average. The mean \( d' \) across subjects on short-lag signal trials equaled only .12, not significantly greater than zero, \( F(1, 3) = 2.13, p > .2 \). Two of the subjects (J.K. and B.F.) had values of \( d' \) well under .1, indicating extremely low guessing sensitivity. The other two subjects (V.S. and S.D.) had somewhat higher values of \( d' \) (.33 and .15, respectively). However, this was due almost entirely to a slightly elevated hit rate for the WW stimuli compared with the NN stimuli. When we recomputed the guessing sensitivity of the latter subjects on the basis only of their hit rates for NN stimuli versus their false-alarm rates for the WN and NW stimuli, the resulting values of \( d' \) all fell below .1, revealing virtually no useful partial information for discriminating positive from negative stimuli following the short-lag signal (see Table 4, top section, boldfaced rows).\(^{24} \)

---

**Table 4**

<table>
<thead>
<tr>
<th>Process &amp; subject</th>
<th>Hit rate (%)</th>
<th>False-alarm rate (%)</th>
<th>Sensitivity (( d' ))</th>
<th>Bias (log ( \beta ))</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Guessing</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>J.K.</td>
<td>19.4</td>
<td>20.9</td>
<td>-0.06</td>
<td>-0.04</td>
</tr>
<tr>
<td>B.F.</td>
<td>69.8</td>
<td>67.7</td>
<td>0.06</td>
<td>-0.03</td>
</tr>
<tr>
<td>V.S.</td>
<td>76.0</td>
<td>64.9</td>
<td>0.33</td>
<td>-0.18</td>
</tr>
<tr>
<td>V.S.</td>
<td>67.1</td>
<td>64.9</td>
<td>0.06</td>
<td></td>
</tr>
<tr>
<td>S.D.</td>
<td>3.8</td>
<td>3.0</td>
<td>0.15</td>
<td>0.18</td>
</tr>
<tr>
<td>S.D.</td>
<td>2.5</td>
<td>3.0</td>
<td>0.11</td>
<td></td>
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<tr>
<td><strong>Guessing</strong></td>
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<td></td>
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<tr>
<td>J.K.</td>
<td>54.6</td>
<td>18.7</td>
<td>0.99</td>
<td>0.39</td>
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<tr>
<td>B.F.</td>
<td>67.9</td>
<td>39.7</td>
<td>0.70</td>
<td>-0.08</td>
</tr>
<tr>
<td>V.S.</td>
<td>69.5</td>
<td>40.2</td>
<td>0.73</td>
<td>-0.10</td>
</tr>
<tr>
<td>S.D.</td>
<td>68.0</td>
<td>8.4</td>
<td>1.89</td>
<td>0.83</td>
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<td><strong>Normal</strong></td>
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<td></td>
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<td></td>
</tr>
<tr>
<td>J.K.</td>
<td>91.4</td>
<td>6.3</td>
<td>3.02</td>
<td>0.25</td>
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<tr>
<td>B.F.</td>
<td>92.9</td>
<td>7.8</td>
<td>3.02</td>
<td>-0.07</td>
</tr>
<tr>
<td>V.S.</td>
<td>94.2</td>
<td>5.9</td>
<td>3.33</td>
<td>-0.01</td>
</tr>
<tr>
<td>S.D.</td>
<td>99.1</td>
<td>1.9</td>
<td>5.19</td>
<td>-0.59</td>
</tr>
</tbody>
</table>

**Note.** The boldfaced rows exclude guesses made in response to word-stimuli. Guessing \(_1\) = guesses on short-lag signal trials; guessing \(_2\) = guesses on long-lag signal trials.

---

For the accuracy of guesses made in response to the various types of test stimuli. The \( d' \) measure represents a pure estimate of the sensitivity in stimulus discriminations achieved by the guessing processes through partial information from the unfinished normal processes.\(^{22} \) The log \( \beta \) measure represents a pure estimate of response bias that depends on idiosyncratic preferences implicit in the guessing processes.\(^{23} \)

The formula for calculating the guessing sensitivity is \( d' = \sqrt{\frac{\text{hit rate}}{\text{false-alarm rate}}} \), where the variables on the right side of this equation are the same as those in Footnote 22 (cf. J. E. K. Smith, 1974). In essence, log \( \beta \) corresponds to a "cut point" on a logarithmic likelihood-ratio scale used to discriminate positive stimuli from negative stimuli. If there were no bias in making guesses about the test stimuli, then \( \beta \) would equal 1 and log \( \beta \) would equal zero. Positive values of log \( \beta \) indicate a bias toward negative responses, and negative values of log \( \beta \) indicate a bias toward positive responses.

The fact that some subjects produced relatively high hit rates in their guesses for the WW stimuli on short-lag signal trials may be understood more fully in terms of their guessing-completion times. For example, consider V.S., who had the highest hit rate in making guesses about the WW stimuli. When the signal lag was short, the median guessing-completion time of V.S. for WW stimuli was 562 ms. His median exceeded those of the other subjects by a considerable amount (e.g., J.K. and B.F. had corresponding median guessing-completion times of 491 and 480 ms, respectively, for WW stimuli). Because of imperfections in our adjustment of the short signal lag, the median guessing-completion time of V.S. on short-lag signal trials also exceeded his own minimum reaction time for WW stimuli on the regular trials (562 ms vs. 465 ms). This time difference was sufficiently great that when WW stimuli were presented to V.S., his normal recognition and comparison processes had about a .15 probability of finishing before the guessing processes induced by the short-lag signal. It is therefore likely that some useful partial information from the normal processes was available to help V.S. make accurate guesses for the WW stimuli, given the relatively large magnitude of his short signal lag. In contrast, the other subjects (e.g., J.K. and B.F.) lacked the advantage enjoyed by V.S., because their short-lag signals occurred sooner, and their guesses were almost always completed before the normal processes finished. This could explain why they failed to guess more accurately about the WW stimuli on short-lag signal trials.
We should stress, nevertheless, that the subjects whose guessing accuracy fell virtually at chance on short-lag signal trials still had median guessing-completion times very close to their minimum reaction times on the regular trials (Figure 13). The guessing processes induced by the signal with the short lag did not finish much ahead of the fastest normal processes. It is therefore of substantial theoretical interest that these subjects had no partial information available for making accurate guesses under such circumstances.

Comparison with normal sensitivity. Finally, it is also of interest to compare the sensitivity and bias of the guessing processes with the sensitivity and bias of the completed normal processes. A signal-detection analysis of response accuracies on regular trials reveals that the completed normal processes were more sensitive than guesses made in response to either the short-lag or long-lag response signals (Table 4, bottom rows; mean $d' = 3.64$). Although the guessing processes induced by the response signal with the long lag enjoyed some partial information for better-than-chance accuracy (mean $d' = 1.08$), this intermediate output was not nearly as large as the amount of information ultimately produced by the completed normal processes. The marked difference in sensitivity between the guessing processes and completed normal processes may have important implications, which we outline more fully later (see General Discussion).

Discussion

Experiment 1 had two main objectives. One was to validate the PSG model on which the speed-accuracy decomposition technique relies. Another was to determine if and when the normal processes of word recognition and lexical-status comparison in the dual-string lexical-decision task produce any useful partial information for accurate guessing before their completion. Both of these objectives were largely achieved.

We obtained considerable evidence supporting the PSG model. For short-lag signal versus long-lag signal trials, the duration of the guessing processes did not vary much as a function of signal lag. Stimulus type, which markedly affected the duration of the normal processes (Figure 13, top panel), did not affect the mean guessing-completion times much on either the short-lag or long-lag signal trials (Figure 13, bottom panel). The absence of stimulus-type effects extended to the mean guessing durations and the interquartile ranges of the guessing-completion times, as expected from the temporal-independence assumption of the PSG model.

We should emphasize again that there was no a priori guarantee that the PSG model would accommodate the reaction time data as well as it did. The distributions of reaction times on the regular and signal trials had to have a special relation to each other for a valid cumulative distribution of guessing-completion times to emerge (see Estimation of Guessing-Completion Times). Many empirical reaction time distributions whose means and variances are qualitatively similar to those observed here would not yield an acceptable decomposition based on Equation 2 of the PSG model (cf. Figure 11). It is therefore encouraging that the present results are reasonably interpretable under the model.

Another major result of Experiment 1 is that partial information appeared to be available for making moderately accurate guesses on the long-lag signal trials. This occurred when the guessing-completion times fell in the same temporal interval as the completion times of the normal processes (i.e., regular-trial reaction times). It would have been impossible to discover the existence of such information without the speed-accuracy decomposition technique because of the confounding otherwise present between the guessing and completed normal processes (cf. Figure 5). The findings that guessing accuracy did exceed chance, and that useful partial information was available from the unfinished normal processes, help validate the full-access assumption of the PSG model.

Given the outcome of Experiment 1, there are new grounds on which to question discrete all-or-none models of word recognition and lexical-status comparison for the dual-string lexical-decision task. We can reject the hypothesis that normal recognition and comparison processes involve a single sharp transition from an initial base level of no information to a final level of high information about correct responses to the positive and negative test stimuli. This follows because the guessing processes induced by the long-lag response signals of Experiment 1 had some partial information with which to achieve better-than-chance accuracy before the normal processes were finished.

Our data regarding the guessing processes on short-lag signal trials suggest, however, that useful partial information did not start accumulating immediately from the onset of a test stimulus. Instead, a relatively long “dormant period” preceded the moment at which better-than-chance guesses were first possible. When the response signal had a nominally short lag, the mean completion time of the guessing processes equaled about 450 ms regardless of stimulus type (Figure 13, bottom panel). We therefore infer that the dormant period preceding partial-information accumulation lasted at least a few hundred milliseconds. Furthermore, the minimum reaction times on regular trials were only around 500 ms (Figure 13, top panel). This means that the normal recognition and comparison processes, which were themselves very accurate, began to be completed within about 50 ms or so later than the guessing processes on short-lag signal trials.

One possible source of the present results might be an abrupt transition in partial information from an initial base level to an intermediate level at the end of the dormant (inaccurate-guessing) period. Perhaps the time course of processing follows a function with multiple steps as illustrated in Figure 6 (middle panel). If the first quantum of partial information becomes available only a few moments before the completion of the normal processes, then this transition could account for the chance guessing accuracy on the short-lag signal trials, even though the fastest normal processes finish almost as quickly as the guessing processes induced by the response signal with the short lag. It could also account for the better-than-chance guessing accuracy on the long-lag signal trials, in which the normal processes have somewhat more time to progress and to accumulate useful partial information before the response signal occurs and the guessing processes begin.

Because there was only one response signal in Experiment 1 for which the guessing accuracy exceeded chance, we cannot draw any further detailed conclusions at this point about the
accumulation of partial information. Several important theoretical questions still remain unanswered. Does partial information produced by the normal processes have any intermediate plateau(s), as a multistate discrete model would predict? Or does partial information increase steadily over an extended period of time once its accumulation has started, consistent with some continuous models? How long does the increase last, and how high does it go? To answer these questions, results must be examined for more response signals at additional time points after the onsets of lexical test stimuli. This was the purpose of Experiment 2.

Experiment 2

We designed Experiment 2 to check for a plateau in the partial information accumulated by the normal processes of word recognition and comparison during the dual-string lexical-decision task. Our approach stemmed from details of the data in Experiment 1. As mentioned previously, Experiment 1 revealed better-than-chance guessing accuracy when the lag of the response signal was long but not when it was short. The long-lag signal induced guesses whose completion times (Figure 13, bottom panel) always exceeded the minimum reaction time for WW stimuli on regular trials (Figure 13, top panel), whereas the completion times of guesses induced by the short-lag signal were always slightly less than this minimum. Given these results, it seemed possible that a partial-information plateau might be found with a combination of signal lags that each yield guessing-completion times greater than the minimum regular-trial reaction times.

Experiment 2 therefore incorporated response signals with two lags, including a medium and a long one. The long-lag signal of Experiment 2 was functionally equivalent to the long-lag signal of Experiment 1. It induced guessing processes whose completion times exceeded the completion times of the normal processes (i.e., regular-trial reaction times) on approximately 50% of the long-lag signal trials during which WW stimuli were presented. For each subject, the medium signal lag was somewhat (viz., between 100 and 150 ms) less than the long lag but greater than the short lag of Experiment 1. Correspondingly, the completion times of the guessing processes induced by the medium-lag signal of Experiment 2 exceeded the completion times of the normal processes on approximately 25% of the signal trials during which WW stimuli were presented. Under these circumstances, the discovery of a partial-information plateau would be consistent with a discrete model having one (or more) intermediate output states, whereas the failure to discover such a plateau would be consistent with at least some continuous models (cf. Table 1).

In addition, Experiment 2 also provided further tests of the PSG model on which speed-accuracy decomposition is based. We again checked the model’s assumption that the normal and guessing processes are temporally independent. Temporal independence and other assumptions of the model (e.g., winner takes all) may be reinforced by determining whether the estimated guessing-completion times remain unaffected by stimulus type and the guessing durations remain unaffected by signal lag.

Method

Subjects. Four students from the same pool as in Experiment 1 served as paid subjects. Three of them (J.K., V.S., and B.Z.) were male and the other (P.C.) was female. The first 2 subjects (i.e., J.K. and V.S.) had also been in Experiment 1.

Apparatus and stimuli. The apparatus and stimuli were the same as before.

Design and procedure. The design and procedure paralleled those of Experiment 1 except for changes made in the lags of the response signals.

Response-signal lags. We placed the response signal with the medium lag such that the guessing processes induced by it had completion times whose magnitudes almost always exceeded the 10th percentile of the reaction time distribution for WW stimuli on regular trials. For each subject, this placement was achieved by tracking the median regular-trial reaction time produced in response to the WW stimuli and by subtracting a value between 220 ms and 340 ms (mean decrement = 290 ms) from that median to set the medium signal lag at the start of each trial block (cf. Experiment 1). The medium lag averaged 480 ms, allowing sufficient time for partial information accumulated by the normal recognition and comparison processes to reach an intermediate plateau.

The response signal with the long lag occurred an average of 110 ms later than the medium-lag signal after the onsets of the test stimuli. We adjusted the long signal lag to be functionally equivalent to the long signal lag in Experiment 1. As a result, the guessing processes finished ahead of the normal processes on approximately 50% of the long-lag signal trials in both experiments.

Data analyses. The data were analyzed in the same way as for Experiment 1.

Results

Regular and signal trials. Some results of Experiment 2 are shown in Table 5 for each trial type and stimulus type. The table includes the mean reaction times of correct responses, mean reaction times of incorrect responses, and response accuracy (percentage of correct responses) averaged across subjects. Performance on the regular and long-lag signal trials followed the same qualitative pattern as found for those trial types during Experiment 1 (cf. Table 2). There were again significant effects of stimulus type (WW, NN, WN, and NW) on the regular-trial reaction times; for example, for correct responses, $F(3, 9) = 9.59, p < .01$. The long-lag signal trials yielded shorter reaction times, $F(1, 3) = 23.0, p < .05$, and lower response accuracy, $F(1, 3) = 40.1, p < .01$, than did the regular trials. Even greater reductions in mean reaction times and response accuracy occurred on the medium-lag signal trials, respectively, $F(1, 3) = 37.4, p < .05$, and $F(1, 3) = 67.8, p < .01$. Nevertheless, on both medium-lag and long-lag signal trials, response accuracy remained at an above-chance level, respectively, $F(1, 3) = 26.2, p < .05$, and $F(1, 3) = 46.8, p < .01$.

More details regarding the reaction times on regular and signal trials appear in Figure 14, which shows Vincented cumulative distributions from a combination of correct and incorrect responses. The top panel (regular-trial reaction times) replicates our previous observation that the effects of stimulus type on the duration of the normal recognition and comparison processes extend throughout the entire time range. The middle panel (signal-trial reaction times) confirms that such effects become less apparent with the presentation of a response signal but that they
Table 5
Results From the Regular and Signal Trials of Experiment 2

<table>
<thead>
<tr>
<th>Trial &amp; stimulus type</th>
<th>Mean reaction time (milliseconds)</th>
<th>Response accuracy (% correct)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Correct responses</td>
<td>Incorrect responses</td>
</tr>
<tr>
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<td></td>
</tr>
<tr>
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<td>Nonword-word</td>
<td>872</td>
<td>838</td>
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<tr>
<td>Signal</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Word-word</td>
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<td>686</td>
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<tr>
<td>Nonword-nonword</td>
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<td>682</td>
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<tr>
<td>Word-nonword</td>
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<td>685</td>
</tr>
<tr>
<td>Nonword-word</td>
<td>676</td>
<td>686</td>
</tr>
</tbody>
</table>

Note. Signal₁ = medium lag; signal₂ = long lag.

The bottom panel of Figure 14 shows Vincentized cumulative distributions of guessing-completion times estimated from Equation 2 of the PSG model for the medium-lag signal trials (left-hand cluster) and long-lag signal trials (right-hand cluster). All of these distributions had approximately the same shape regardless of stimulus type and signal lag. Some additional details regarding the guessing-completion times, including their means and interquartile ranges, appear in Table 6. Consistent with the PSG model’s temporal-independence assumption, there were no significant effects of stimulus type on the means, $F(3, 9) < 1.0$, $p > .5$. There was a marginally reliable effect of signal lag on the interquartile ranges, $F(3, 9) < 1.0$, $p > .5$, of the guessing-completion times. Likewise, signal lag did not affect the mean guessing durations significantly, $F(1, 3) < 1.0$, $p > .5$. There was a marginally reliable effect of signal lag on the interquartile ranges of the guessing-completion times, $F(1, 3) = 8.52$, $.05 < p < .1$. However, this effect was small (viz., 13 ms) in absolute magnitude. The only substantial lag effect occurred for the mean guessing-completion times. When the response signal had a medium lag, the guesses took 108 ms more time to be completed on the average than when the signal had a medium lag. This difference is almost exactly the same magnitude as the mean difference of 110 ms between the lengths of the two signal lags, which we would expect if the guessing and normal processes are temporally independent. The good fit of the data to the temporal-independence assumption adds credibility to the PSG model.

More important, the medium signal lag achieved the relation that we intended between the guessing-completion times and the reaction times for WW stimuli on regular trials. When the response signal had a medium lag, the guessing processes induced by it almost always finished later than the 10th percentile of the cumulative distribution associated with WW regular-trial reaction times (Figure 14, top and bottom panels). Compared to what happened on the short-lag signal trials of Experiment 1, the normal recognition and comparison processes on the medium-lag signal trials of Experiment 2 were allowed significantly more time to reach a partial-information plateau before being interrupted (cf. Figure 13). This means the guessing accuracies found in Experiment 2 for the medium and long signal lags may provide additional evidence about the existence of an intermediate partial-information plateau.

**Guessing accuracy.** Table 6 shows the accuracy of the guessing processes estimated from Equation 4 of the PSG model as a function of signal lag for each type of test stimulus, averaged across subjects. On both medium-lag and long-lag signal trials, the guesses induced by the response signals were better than chance, respectively, $F(1, 3) = 16.4$, $p < .05$, and $F(1, 3) = 17.3$, $p < .05$, just as happened with the long-lag signal of Experiment 1. The length of the signal lag in Experiment 2 did not affect the mean guessing accuracy significantly, $F(1, 3) < 1.0$, $p > .5$. As the lag increased, the mean guessing accuracy changed by only $-0.1\%$ (i.e., 62.4 vs. 62.3%). This outcome suggests the existence of an intermediate partial-information plateau at a relatively advanced phase of the normal recognition and comparison processes.

**Guessing sensitivity and bias.** Further evidence of a partial-information plateau is presented in Table 7 (top and middle rows). Here the accuracy of the guessing processes has been converted to separate measures of sensitivity ($d'$) and bias (log $\beta$) for each subject on the basis of an analysis like the one reported earlier (cf. Table 4). These results allow the guessing sensitivity and bias to be assessed as a function of signal lag.

We found that the signal lag had virtually no effect on guessing sensitivity averaged across subjects; for long-lag versus medium-lag signal trials, the mean difference in $d'$ was only $-0.02$, $F(1, 3) < 1.0$, $p > .5$. One subject (B.Z.) exhibited a slight in-
crease in \(d'\) over time (mean change = .11), but the other three subjects (J.K., V.S., and P.C.) all exhibited slight decreases (mean change = -.06). This pattern is what we would expect if the guessing processes have access to a stable level of partial information during a temporal interval in which the normal processes of word recognition and lexical-status comparison are in a final phase of being completed.

Like the mean guessing sensitivity, the mean response bias of the guessing processes changed relatively little as a function of signal lag. \(F(1, 3) < 1.0, p > .5\). The values of log \(\beta\) averaged across subjects equaled .35 and .33, respectively, when the response signal had medium and long lags, reflecting a stable tendency toward making negative guesses. The absence of a change in bias is consistent with the existence of a partial-information plateau over the temporal interval bounded by the onsets of the medium-lag and long-lag response signals.

**Comparison with normal sensitivity and bias.** It is also interesting to compare the sensitivity of the guessing processes with the sensitivity of the completed normal processes. As the bottom rows of Table 7 indicate, the completed normal processes on regular trials had a considerably greater level of sensitivity (mean \(d'\) = 2.82) than was achieved by the guessing processes on the medium-lag and long-lag signal trials (mean \(d'\) = .72). We found the same result in Experiment 1 (cf. Table 4). The guessing sensitivity only reached about 25% of the ultimate sensitivity attained by the normal processes. It appears that the information provided by the normal processes to the guessing processes is indeed "partial" and that a final large change in available information may occur at the end of the normal processes.

Similar conclusions are also suggested by analyses of the response bias (log \(\beta\)) associated with the guessing processes and completed normal processes (Table 7, last column). Whereas a marked bias toward negative responses occurred in the guessing processes during both medium-lag and long-lag signal trials, the completed normal processes were relatively unbiased on the regular trials (mean log \(\beta\) = .05). This difference in response bias, like the accompanying difference in sensitivity, suggests a final large increment in the information used by the normal processes for selecting and executing overt responses.

**Discussion**

Experiment 2 adds several instructive pieces of data to those obtained already in the dual-string lexical-decision task. For response signals with both medium and long lags, the observed reaction times and the estimated distributions of guessing-completion times were reasonably consistent with the PSG model. The guessing processes hypothesized under the model again had access to useful partial information from normal recognition and comparison processes when the guessing-completion times exceeded the time taken to complete the fastest normal processes (i.e., minimum regular-trial reaction times). We found that during a temporal interval when partial information was available...
available for making accurate guesses, the mean accuracy of the guessing processes remained relatively constant over time, suggesting a plateau in the amount of partial information produced by the as yet unfinished normal processes. Such a partial-information plateau would not have been discovered without speed-accuracy decomposition of the combined results from the regular and signal trials. Even though the guessing accuracy remained essentially constant as a function of signal lag during Experiment 2, the overall response accuracy was significantly greater on long-lag signal trials than on medium-lag signal trials (i.e., 74% vs. 67%), owing to an increase in the frequency with which the normal processes beat the guessing processes (Table 6).

Thus, a picture has emerged that is consistent with a multistate discrete model for the dual-string lexical-decision task. This resolution supplements some of our previous results obtained with the nominally short signal lag in Experiment 1. There we demonstrated that during an extended dormant period after the onset of lexical test stimuli, no useful partial information was available from the normal processes of word recognition and lexical-status comparison. Our subjects did not produce better-than-chance guesses until around the same time as responses based on the fastest normal processes would have started to emerge (i.e., minimum regular-trial reaction time). The long dormant period, followed by a rather abrupt transition to a partial-information plateau, is what one would expect with a multistate discrete model (Figure 6, middle panel).

Nevertheless, many issues remain open to debate in light of the results from Experiments 1 and 2. One might argue, for example, that our first two experiments were not sufficiently thorough attempts at examining the internal states and outputs of information processing for the dual-string lexical-decision task. So far we have only examined performance involving three different response-signal lags (i.e., short, medium, and long). Perhaps this limited number of lags failed to provide enough power for differentiating between predictions made by multistate discrete models and continuous models. Consequently, we have conducted a third experiment involving a larger complement of signal lags.

Experiment 3

Experiment 3 replicated and extended the results of Experiments 1 and 2 concerning the onset and time course of partial-information accumulation in the dual-string lexical-decision task. Rather than including only two or three different response signals, we used a total of five during Experiment 3. One of these signals was adjusted to be functionally equivalent to the short-lag signal of Experiment 1; it induced guessing processes whose median completion time was, on the average, about 85 ms less than the minimum regular-trial reaction time for WW test stimuli. This constraint yielded a lag that equaled approximately 150 ms averaged across subjects.

The onsets of the other four response signals were adjusted by tracking the median regular-trial reaction time obtained with WW stimuli and subtracting different preset amounts from it. As a result, s1, s2, s3, s4, and s5 had mean lags of about 425, 475, 525, and 575 ms, respectively. These lags yielded guessing processes whose median completion times fell roughly at the 20th, 30th, 50th, and 60th percentiles of the regular-trial reaction time distribution for WW stimuli. In each case, the response signals other than s5 never induced guessing processes whose completion times were less than the minimum regular-trial reaction time. This helped ensure that the points obtained on the partial-information accumulation function would have a good chance of revealing an intermediate plateau, if one actually exists.

Data analyses. The data analyses were the same as in Experiments 1 and 2.

Results

Regular and signal trials. Some results from the regular and signal trials of Experiment 3 appear in Table 8, which shows the mean reaction times of correct responses, mean reaction times of incorrect responses, and response accuracy as a function of stimulus type and signal lag. Subjects' performance was qualitatively similar to what occurred in the previous two experiments (cf. Tables 2 and 5). There were again significant stimulus-type effects on regular-trial reaction times; for example, for WW versus WN, F(1, 6) = 9.24, p < .05. The response signals decreased reaction times, increased error rates, and diminished the effects of stimulus type (p < .05 in all cases).
Further details regarding the reaction times on regular and signal trials appear in Figure 15. Here we have plotted Vincenitized cumulative distributions of regular-trial reaction times (top panel) and signal-trial reaction times (middle panel) as a function of stimulus type and signal lag. These distributions look similar to those found in the previous two experiments (cf. Figures 13 and 14). Stimulus-type effects occurred throughout most of the regular-trial time range. Decreasing the signal lag on signal trials shifted the signal-trial distributions toward the lower end of the time scale and steepened them considerably. As a result, there are now additional grounds for drawing inferences about the nature of the normal and guessing processes in the dual-string lexical-decision task.

**Guessing-completion times and durations.** Estimated distributions of guessing-completion times, which come from applying Equation 2 to the regular-trial and signal-trial distributions of reaction times, are shown in Figure 15 (bottom panel) as a function of stimulus type and signal lag for Experiment 3. The guessing-completion time distributions appear clumped into five distinct groups, each of which represents the guessing processes induced by one of the five response signals. As the signal lag decreased, it shifted the guessing-completion time distributions toward the lower end of the time scale, but there were no substantial lag effects on the shapes of these distributions, nor were there any substantial stimulus-type effects. The clumping of the guessing-completion time distributions as a function of signal lag is especially salient in comparison with the signal-trial and regular-trial reaction time distributions (cf. Figure 15, middle and top panels), which exhibited a much less compact configuration for the various test stimuli and for the response signals that had relatively long lags (i.e., $s_2$ through $s_5$). This is

Note. Signal trials are subscripted in order of ascending signal lag.

### Table 8

Results From the Regular and Signal Trials of Experiment 3

<table>
<thead>
<tr>
<th>Trial &amp; stimulus type</th>
<th>Mean reaction time (milliseconds)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Correct responses</td>
</tr>
<tr>
<td>Regular</td>
<td></td>
</tr>
<tr>
<td>Word-word</td>
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<tr>
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<td>$S_1$</td>
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<tr>
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<td>Nonword-word</td>
<td>716</td>
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</table>

The only apparent lag effect on the shapes of the guessing-completion time distributions occurred with the two longest signal lags (i.e., $s_4$ and $s_5$). In this case, the lower tails of the distributions were somewhat lengthened, yielding relatively small minima. However, such lengthening was restricted to the interval below the distributions’ 15th percentiles.
what we would expect under the temporal-independence and
winner-takes-all assumptions of the PSG model (Figure 12).

Corresponding to the bottom panel of Figure 15, Table 9
shows the means and interquartile ranges of the guessing-com-
pletion times along with the mean guessing durations. Again
supporting the temporal-independence assumption, neither
stimulus type nor signal lag affected the interquartile ranges
significantly, respectively, $F(3, 6) < 1.0, p > .5$, and $F(4, 8) < 1.0,
p > .5$. Also, stimulus type did not affect the mean guessing-
completion times significantly, $F(3, 6) = 1.28, p > .3$. The mean
guessing-completion times induced by the response signals that
had moderate to long lags (i.e., $s_2$ through $s_5$) were separated by
about the same amounts as the objective differences between
the lengths of these lags (i.e., 50 ms per pair of adjacent lags).

There was a significant effect of signal lag on the mean guessing
durations, $F(4, 8) = 335, p < .001$. However, most of this effect
occurred in the mean guessing duration for the signal with the
shortest lag (i.e., $s_1$) versus the mean guessing durations for the
other signals. Response signal $s_1$ yielded a mean guessing dura-
tion of 239 ms. The other signals with longer lags yielded guess-
ing durations whose means all hovered around 200 ms. Thus,
at least for the longer lags, the temporal-independence assump-
tion of the PSG model seems to be reasonably valid.

**Guessing accuracy.** Some results regarding the accuracy of the
guessing processes also appear in Table 9 (last column).

There was a significant effect of signal lag on the guessing accuracy
averaged across test stimuli and subjects, $F(4, 8) = 15.9,
p < .01$. However, this lag effect can be attributed almost en-
tirely to a difference between the mean guessing accuracy ob-
tained with the shortest lag ($s_1$) and the mean guessing accuracies
obtained with the longer lags ($s_2$ through $s_5$). When the
response signal had the shortest lag, the mean guessing accuracy
was only 52.9%, falling virtually at the chance (i.e., 50%) level.

In contrast, when the response signals had longer lags, the mean
guessing accuracy was 68.8%, substantially above chance, $F(1,
2) = 29.9, p < .05$. The guessing accuracies obtained with sig-
nals $s_2$ through $s_5$ did not vary significantly as a function of
signal lag; they were all around 69% ($F(3, 8) < 1.0, p > .5$). This
reinforces our previous inference that the normal processes of
word recognition and lexical-status comparison reach a partial-
information plateau found for the guessing processes with relatively
long signal lags.

There was also at least moderate stability over time in the
response bias exhibited by the guessing processes of some sub-
jects for signals $s_2$ through $s_5$. One subject (R.F.) had uniform
positive values of $\log \beta$ when the signal lags were relatively long,
indicating a consistent bias toward negative responses (mean $\log \beta = .22$). Another subject (R.D.) had uniform negative log

### Table 9

<table>
<thead>
<tr>
<th>Trial &amp; stimulus type</th>
<th>Completion time (milliseconds)</th>
<th>Duration (milliseconds)</th>
<th>Inter-quartile range (milliseconds)</th>
<th>Accuracy (%)</th>
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*Note.* Signal trials are subscripted in order of ascending signal lag.

$\beta$ values, indicating a consistent bias toward positive responses
(mean $\log \beta = -.10$). The third subject (C.H.) had a combination
of positive and negative log $\beta$ values, depending on signal
lag.

**Comparison with normal sensitivity.** As before, the com-
pleted normal processes were substantially more sensitive than
the guessing processes (mean $d' = 3.09$ vs. 0.98), even when the
guessing processes occurred after the longest signal lag, $F(1,
2) = 4515, p < .001$. This difference reinforces our previous
conclusion that the information provided by the unfinished
normal processes to the guessing processes is truly partial. The
ultimate information level reached by the completed normal
processes embodies a marked increment over the partial-infor-
mation plateau found for the guessing processes with relatively
long signal lags.

**Discussion**

Experiment 3 achieved its major objectives. The results de-
“

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Table 9: Results Regarding the Guessing Processes on Signal Trials in Experiment 3.
Table 10

Signal-Detection Analysis of the Guessing and Normal Processes in Experiment 3

<table>
<thead>
<tr>
<th>Process &amp; subject</th>
<th>Hit rate (%)</th>
<th>False-alarm rate (%)</th>
<th>Sensitivity ($d'$)</th>
<th>Bias ($log\beta$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Guessing\textsubscript{1}</td>
<td>C.H.</td>
<td>66.3</td>
<td>58.8</td>
<td>0.19</td>
</tr>
<tr>
<td></td>
<td>R.D.</td>
<td>95.3</td>
<td>93.1</td>
<td>0.23</td>
</tr>
<tr>
<td></td>
<td>R.F.</td>
<td>34.1</td>
<td>26.2</td>
<td>0.23</td>
</tr>
<tr>
<td>Guessing\textsubscript{2}</td>
<td>C.H.</td>
<td>61.3</td>
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<td>0.87</td>
</tr>
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<td></td>
<td>R.D.</td>
<td>32.1</td>
<td>34.0</td>
<td>0.74</td>
</tr>
<tr>
<td></td>
<td>R.F.</td>
<td>66.1</td>
<td>20.1</td>
<td>1.23</td>
</tr>
<tr>
<td>Guessing\textsubscript{3}</td>
<td>C.H.</td>
<td>70.1</td>
<td>22.1</td>
<td>1.27</td>
</tr>
<tr>
<td></td>
<td>R.D.</td>
<td>65.9</td>
<td>39.5</td>
<td>0.65</td>
</tr>
<tr>
<td></td>
<td>R.F.</td>
<td>62.3</td>
<td>18.6</td>
<td>1.18</td>
</tr>
<tr>
<td>Guessing\textsubscript{4}</td>
<td>C.H.</td>
<td>77.9</td>
<td>33.5</td>
<td>1.17</td>
</tr>
<tr>
<td></td>
<td>R.D.</td>
<td>70.1</td>
<td>52.5</td>
<td>0.45</td>
</tr>
<tr>
<td></td>
<td>R.F.</td>
<td>68.3</td>
<td>20.1</td>
<td>1.29</td>
</tr>
<tr>
<td>Guessing\textsubscript{5}</td>
<td>C.H.</td>
<td>62.5</td>
<td>22.6</td>
<td>1.05</td>
</tr>
<tr>
<td></td>
<td>R.D.</td>
<td>63.7</td>
<td>40.6</td>
<td>0.56</td>
</tr>
<tr>
<td></td>
<td>R.F.</td>
<td>73.6</td>
<td>25.3</td>
<td>1.26</td>
</tr>
<tr>
<td>Normal</td>
<td>C.H.</td>
<td>94.9</td>
<td>9.0</td>
<td>3.15</td>
</tr>
<tr>
<td></td>
<td>R.D.</td>
<td>90.4</td>
<td>8.7</td>
<td>2.76</td>
</tr>
<tr>
<td></td>
<td>R.F.</td>
<td>94.4</td>
<td>5.7</td>
<td>3.37</td>
</tr>
</tbody>
</table>

Note. The guessing processes are subscripted in order of ascending signal lag.

provided by the normal processes of word recognition and lexical-status comparison to concurrent guessing processes for the dual-string lexical-decision task. Consistent with previous data from Experiments 1 and 2, this plateau occurred over a time interval during which the normal and guessing processes each had a significant probability of finishing their race. Nevertheless, there appeared to be a substantial dormant period before much, if any, useful information emerged from the normal processes after the onset of the test stimuli. When the guessing processes had completion times that were just a bit less than those of the fastest normal processes (i.e., minimum regular-trial reaction time), the guessing accuracy still remained very near the chance level.

A concise summary of our findings for the dual-string lexical-decision task appears in Figure 16. Here we have plotted the mean accuracy of the guessing processes (solid circles) as a function of the mean guessing-completion times for Experiment 3. The figure includes five distinct accuracy-versus-time points, corresponding to the five different lags used during the signal trials. On the horizontal axis, there is also a marker indicating the minimum regular-trial reaction time (i.e., shortest normal-process completion time) for WW stimuli. As the dashed step function indicates, the guessing accuracies are consistent with an abrupt transition in accumulated partial information. The focus of this transition may be closely correlated with events that take place shortly before the completion of the fastest normal processes. Figure 16 looks much like what one would expect from a three-state discrete model whose intermediate output is a single partial-information quantum (cf. Figure 6, middle panel).

We should emphasize once again that it would have been impossible to discover this underlying pattern of accumulated partial information without speed-accuracy decomposition. A standard plot of response accuracy versus signal lag (i.e., speed-accuracy trade-off curve) for the signal trials of Experiment 3 provides no evidence of a partial-information plateau. As mentioned above, the response accuracy on signal trials increased monotonically with the length of the lag (Table 8), ranging from a low value of 52.9% through intermediate values of 73.1%, 77.0%, and 79.3% to the relatively high value of 81.6%. To determine the form of the partial-information accumulation function, the contributions made by completed normal processes had to be removed from these accuracy values, revealing the residual accuracy associated with the guessing processes.

It remains to be determined whether special cases of continuous models might account for the present results. Through judicious selection and elaboration of basic assumptions, there are various ways of making continuous models closely mimic discrete ones (e.g., McClelland, 1979; Meyer, Yantis, Osman, & Smith, 1985; J. Miller, 1982a; Ratcliff, 1988). For example, the stochastic diffusion model can yield an intermediate partial-information plateau similar to the one in Figure 16 (Ratcliff, 1988). The choice between alternative theoretical frameworks then becomes one involving matters of plausibility, parsimony, and generality as well as empirical goodness of fit. We will have more to say about these matters later, and we will further consider how specific discrete and continuous models could be extended in light of our data. However, before this general discussion, two additional experiments with the speed-accuracy decomposition technique merit some attention.

Figure 16. Mean guessing accuracy (solid circles) versus mean guessing-completion time for the five signal lags in Experiment 3 with the dual-string lexical-decision task. (The marker on the horizontal axis indicates the minimum regular-trial reaction time for word-word stimuli, which reflects the completion time of the fastest normal processes. The dashed step function corresponds to the intermediate output of a hypothetical three-state discrete model [cf. Figure 6, middle panel].)
Experiment 4

The purpose of Experiment 4 was to obtain additional clarification regarding subjects' performance on the regular (nonsignal) trials of the TRT procedure. In developing the speed-accuracy decomposition technique and applying it to the dual-string lexical-decision task, we have claimed that results from the regular trials reflect normal processes of word recognition and lexical-status comparison. This claim implies a strong qualitative similarity between the processing strategies adopted by subjects in the present experiments and in conventional reaction time procedures. For the findings of Experiments 1 through 3 to be extended to the present context, it is important that such similarity actually holds. Mixing signal trials with regular procedures for the findings of Experiments 1 through 3 to be generalized beyond the present context, it is important that such similarity actually holds. Mixing signal trials with regular procedures should not alter the normal processes; they should be the same as those that take place on regular trials when no response signals are expected. We have therefore conducted Experiment 4 with a view toward determining whether the relative frequency of signal trials has any serious effects on regular-trial reaction times and accuracy levels, which would suggest a lack of normal-process invariance.

Two types of trial blocks, mixed and pure, were included in Experiment 4. The mixed blocks contained randomly interleaved regular and signal trials, paralleling the TRT procedure of Experiments 1 through 3. The pure blocks contained only regular trials. For each block type, we measured subjects' reaction times and response accuracy on the regular trials as a function of the TRT procedure and applying it to the dual-string lexical-decision task, we have claimed that results from the regular trials reflect normal processes of word recognition and lexical-status comparison. This claim implies a strong qualitative similarity between the processing strategies adopted by subjects in the present experiments and in conventional reaction time procedures. For the findings of Experiments 1 through 3 to be extended to the present context, it is important that such similarity actually holds. Mixing signal trials with regular procedures should not alter the normal processes; they should be the same as those that take place on regular trials when no response signals are expected. We have therefore conducted Experiment 4 with a view toward determining whether the relative frequency of signal trials has any serious effects on regular-trial reaction times and accuracy levels, which would suggest a lack of normal-process invariance.

The logic of Experiment 4 is as follows. Suppose the normal processes of word recognition and lexical-status comparison are qualitatively similar in the TRT procedure and in conventional reaction time procedures. Then the reaction times and accuracy levels on the regular trials of the mixed and pure blocks, which reflect those processes, should not differ much as a function of block type. Also, more important, the effects of major independent variables such as test-stimulus type should be about the same regardless of block type. In contrast, if the mixture of signal and regular trials alters the normal processes qualitatively, then one might expect different patterns of factor effects and different levels of performance to emerge from the pure and mixed blocks.

Method

Subjects. Three students who were in the previous experiments served as paid subjects. They included J.K. and V.S. from Experiment 1 together with B.Z. from Experiment 2.

Apparatus and stimuli. The apparatus and stimuli were the same as those in the previous experiments.

Design. The pure blocks of regular trials for Experiment 4 were administered contiguously with the mixed blocks of regular and signal trials in Experiments 1 and 2. Following the initial practice sessions, each subject went through four test sessions. A test session contained four blocks of mixed regular and signal trials, as described earlier (see Method, Experiments 1 and 2), plus four blocks of pure regular trials. The pure and mixed blocks alternated cyclically during the test sessions. In each mixed block, there were 32 regular trials and 48 signal trials. In each pure block, there were 40 regular trials and no signal trials.

Procedure. The procedure on the mixed blocks was described earlier (see Experiments 1 and 2). Subjects were instructed before each mixed block that they would receive a random combination of regular and signal trials. Subjects were instructed before each pure block that they would receive only regular trials and that there would be no response signals. In other respects, however, the regular trials of the pure blocks were exactly like those of the mixed blocks. The same feedback and payoff contingencies applied with respect to the regular trials of each block type. Also, the selection of test stimuli, presentation of warning signals, and timing of responses were the same. These features helped preclude spurious variation of the normal recognition and comparison processes across the different types of blocks.

Results

Some results of Experiment 4 appear in Table 11. Here we have summarized the mean reaction times and accuracy levels (percentages of correct responses) for the regular trials of each block type (mixed vs. pure) as a function of stimulus type and word frequency. Corresponding results for the signal trials from the mixed blocks may be found in the results sections of Experiments 1 and 2, where the performance of subjects J.K., V.S., and B.Z. has been discussed already (e.g., see Tables 4 and 7). For present purposes, we are most interested in determining if, when, and how the normal processes of word recognition and lexical-status comparison were affected by mixing signal trials with the regular trials. This may be done by examining the main effects of block type on subjects' regular-trial performance and by examining the interactions between block type, stimulus type, and word frequency.

Effects of block type. Block type (pure vs. mixed) had a significant main effect on regular-trial reaction times. Mean reaction times to classify the test stimuli of the regular trials averaged about 9.5 ms less for mixed blocks than for pure blocks (827 ms vs. 922 ms), $F(1, 2) = 29.1, p < .05.$ Correspondingly, the mean accuracy level was about 2.6% lower for mixed blocks.
than for pure blocks (91.8% vs. 94.4%), \( F(1, 2) = 6.57, p > .1 \). This latter outcome, although not statistically reliable, suggests a possible speed–accuracy trade-off across the regular trials of the two block types. When response signals were expected, it appears that subjects sought to produce shorter regular-trial reaction times at the expense of making slightly more errors; they may have adjusted their normal recognition and comparison processes to be less conservative than on the regular trials of the pure blocks. However, it is not yet clear whether this adjustment entailed a qualitative change of processing strategy or a mere fine tuning of component parameters. To resolve the issue, one must look more closely at whether the effects of block type interacted significantly with those of other factors such as test-stimulus type and word frequency, which presumably reflect the detailed nature of the normal processes.

**Effects of test-stimulus type.** As before (cf. Experiments 1 through 3), the mixed and pure blocks of regular trials included four types of test stimuli: WW, NN, WN, and NW. Stimulus type again had significant main effects on regular-trial reaction times, \( F(3, 6) = 9.05, p < .05 \). For example, mean reaction times were about 105 ms shorter on the average in response to WW stimuli than in response to NN stimuli.

Of more importance, the stimulus-type effects remained reasonably consistent across the mixed and pure trial blocks. This consistency is illustrated in Figure 17, which shows the mean regular-trial reaction times for each stimulus type as a function of block type (mixed vs. pure). The block-type and stimulus-type factors did not interact significantly, \( F(3, 6) = 1.14, p > .4 \). We therefore infer that mixing signal trials with the regular trials did not qualitatively alter those components of the normal processes most directly involved in word recognition and lexical-status comparison.

**Effects of word frequency.** Such normal-process invariance is likewise suggested by observed effects of word frequency on regular-trial performance across the mixed and pure blocks. In particular, consider Figure 18, which shows the mean reaction times for WW stimuli as a function of word frequency on the regular trials of the mixed and pure blocks. The two indicated frequency levels, high and low, correspond respectively to pairs of words whose component members each had median frequencies of either 107 occurrences or 2 occurrences per million (Kučera & Francis, 1967). We found that word frequency affected the reaction time means significantly. On the average, responses to WW stimuli were about 180 ms faster for pairs of high-frequency words than for pairs of low-frequency words, \( F(1, 2) = 49.0, p < .05 \), confirming reports by previous investigators about word-frequency effects (e.g., Rubenstein et al., 1971). The present effect of word frequency did not interact significantly with block type; there was only a .4-ms difference between the frequency effects obtained with WW stimuli on mixed and pure blocks, \( F(1, 2) < 1.0, p > .5 \). Similarly, the word-frequency effects did not change significantly across the different block types for any of the other stimulus types (i.e., WN, NW, and NN; \( p > .1 \) in all cases). It therefore appears that those components of the normal recognition and comparison processes in which word frequency had an effect remained the same regardless of whether response signals were expected.

**Discussion**

The results of Experiment 4 provide additional grounds for assessing the extent to which performance on the regular trials of the TRT procedure involves truly normal recognition and comparison processes. Two types of trial blocks, mixed and pure, were included in the experiment. The mixed blocks contained signal trials as well as regular trials, whereas the pure blocks contained only regular trials. Consequently, the pure blocks can be viewed as a direct analog of conventional reaction time procedures, which presumably entail normal processes. By comparing regular-trial performance across the two block types, we get a better picture of whether mixing signal trials with the regular trials markedly alters subjects’ typical processing strategies.

We found some evidence that processing on regular trials does not remain completely invariant as the frequency of signal trials increases. During the mixed blocks, subjects tended to make relatively fast responses at the expense of slightly reduced accuracy even when no response signals actually occurred. Nevertheless, other major independent variables such as test-stimulus type and word frequency had effects whose magnitudes stayed about the same regardless of block type (Figures 17 and 18).

The present data suggest that the contextual influence of the signal trials on regular-trial performance is limited in scope. Some parameters of ancillary normal-process components may be adjusted slightly in going from a conventional reaction time procedure to the TRT procedure with signal trials, but the key characteristics of word recognition and lexical-status comparison do not appear to change qualitatively. If valid, this conclusion bodes well for generalizing our inferences from speed–accuracy decomposition to other situations involving conventional reaction time procedures.

**Interpretation based on a discrete stage model.** A more detailed theoretical interpretation of the results from Experiment 4 is possible in terms of a discrete stage model for word recognition and lexical-status comparison. Suppose that discrete stages with quantal outputs mediate the normal processes used to perform the dual-string lexical-decision task. Then following S. Sternberg’s (1969) additive-factor method, we would infer that the effects of block type (pure vs. mixed) are localized in a processing stage separate from those in which the factors of stimulus type (i.e., WW, NN, WN, and NW) and word frequency (i.e., high vs. low) have their effects. For example, word frequency and stimulus type might influence a relatively early lexical-access stage (Meyer & Schvaneveldt, 1971; Rubenstein et al., 1971), while block type (pure vs. mixed) might influence a subsequent response selection or execution stage. The prospec-

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26 Interestingly, there were modest effects of word frequency even for the NN stimuli, which contained only nonwords. The mean reaction times of responses to the NN stimuli tended to increase with the frequency of the words from which the nonwords came, \( F(1, 3) = 10.4, p < .1 \). This was the reverse of what happened for WW stimuli, which yielded decreasing reaction times as word frequency increased. The reversal may have occurred because nonwords constructed from high-frequency words seem more wordlike and are therefore more difficult to classify as nonwords.
Figure 17. Mean reaction time for each stimulus type on pure blocks (solid bars) and mixed blocks (cross-hatched bars) in Experiment 4 with the dual-string lexical-decision task. (WW = word-word, NN = non-word-nonword, WN = word-nonword, NW = nonword-word.)

Meyer, Yantis, Osman, & Smith (1985). Such priming would explain why mixing the regular and signal trials did not significantly change the word-frequency and stimulus-type effects on regular trials, even though regular-trial reaction times and accuracy both decreased when signal trials were expected.27

This explanation is consistent with results reported by Dickman and Meyer (1988). Using a conventional reaction time procedure, they studied differences in the information-processing strategies of high, medium, and low impulsive subjects, who were selected through a standard personality questionnaire. The subjects had to perform a choice-reaction task involving simple visual stimuli and manual responses. As part of the task,

27 A similar explanation may be reached in terms of the stochastic diffusion model proposed by Ratcliff (1978, 1988). Under this model, effects of block type (mixed vs. pure) on regular-trial performance could occur if subjects respectively lower or raise their response-strength thresholds, depending on whether they expect occasional signal trials. Such adjustments would yield faster, less accurate responses for the regular trials of mixed blocks than for the regular trials of pure blocks, because the drift of response strength would tend to terminate sooner and reach the wrong threshold more often. However, for block type and other factors to affect reaction times additively, as we observed, the effects of stimulus type (i.e., WW, NN, WN, and NW) and word frequency would have to occur before the response-strength drift begins. If stimulus type and word frequency did not have their effects relatively early, but instead altered the drift rate or strength thresholds, then they would interact with block type. So as in our explanation based on the discrete stage model, we are led to conclude that important normal-process components remain unaltered by the mixing of regular and signal trials.
response complexity was varied; in one condition, each response required a single keypress, whereas in another condition, each response required multiple keypresses. The response-complexity factor affected the difficulty of selecting and executing the responses. Dickman and Meyer (1988) found that the effects of response complexity tended to interact with their subjects' impulsivity level. Low impulsives experienced a somewhat greater response-complexity effect than did medium and high impulsives. Given that impulsivity is a personality trait associated with speed-accuracy trade-offs, the obtained interaction supports our conjecture about the locus of block-type (pure vs. mixed) effects on regular-trial performance. It appears that response selection and execution may be generally sensitive to factors that influence subjects' biases toward trading accuracy for speed.

Relevance to the PSG model. The results of Experiment 4 are also relevant to details of the PSG model on which speed-accuracy decomposition rests. In particular, consider Figure 19. This figure shows Vincentized cumulative distributions of reaction times obtained with WW test stimuli on the regular trials of the mixed blocks (dashed function) and pure blocks (solid function). These distributions have some features similar to those predicted by the PSG model for reaction times on the signal trials versus reaction times on the regular trials of the TRT procedure (cf. Figure 10). Mixing signal trials with the regular trials caused the distribution of regular-trial reaction times to have an initially steeper rise and to be shifted toward the low end of the time scale, mimicking the effects of response signals on signal-trial reaction times.

However, the regular-trial reaction times from the pure and mixed blocks do not yield a legitimate derived distribution of guessing-completion times. If we treat the mixed-block data in Figure 19 as a distribution of signal-trial reaction times, then the result of submitting them to Equation 2 from the PSG model is an illegitimate distribution illustrated by the dotted function in Figure 19, which exhibits an initial rise but then becomes nonmonotonic and levels off without reaching a value of one. The nonmonotonicity stems from the fact that although block type had a marked effect on the regular-trial reaction times, the distributions for pure and mixed blocks (i.e., solid and dashed functions) do not satisfy the property of hazard-function dominance. This absence of hazard-function dominance documents our claim that obtaining reaction time distributions to which the PSG model can be applied successfully is not a trivial matter (cf. Figures 10 and 11).

Given that the reaction time distributions in Figure 19 fail to yield a legitimate derived distribution of guessing-completion times, we may reach some further interesting theoretical conclusions. The effect of block type does not stem merely from implicit guessing processes that race with the normal processes on the regular trials of mixed but not pure blocks. Instead, the block-type effect must be attributed to some other source (e.g., changes in response selection or execution) within the normal processes themselves, as argued earlier. Consistent with assumptions made by the PSG model, the guessing processes only seem to enter the picture and race with the normal processes when response signals are explicitly presented on the signal trials.

Experiment 5

Experiment 5 was designed to demonstrate another attractive feature of speed-accuracy decomposition. The decomposition technique can uncover systematically different patterns of accumulated partial information, depending on the particular types of test stimuli and cognitive tasks that subjects must perform. To illustrate this feature, we switched from the dual-string lexical-decision task to a single-string lexical-decision task. The subjects of Experiment 5 made yes-no lexical decisions about individual words and nonwords, producing a separate response for each letter string. They did not directly compare the lexical status of one string with another. Switching the task requirements let us examine information processing under a new set of circumstances in which one might expect the form of the obtained partial-information accumulation function to differ from what was previously found.

Specifically, we expected that speed-accuracy decomposition of results from the single-string lexical-decision task might reveal a steady increase of accumulated partial information rather than an intermediate partial-information plateau. The rationale for this expectation has been outlined earlier (see

Our results contrast with those reported by some investigators who have studied subjects' performance in simple-reaction tasks (i.e., ones with a single stimulus and response). For example, Oilman and Billington (1972) proposed a "deadline" model of such performance. The deadline model assumes an implicit guessing process that races with "normal" processes regardless of whether there is an external response signal to trigger the race. We found no support for this assumption in the present study when a choice-reaction task was involved and results from regular (i.e., nonsignal) trials of mixed versus pure blocks were analyzed.
Overview of Experiments. In the single-string lexical-decision task, the mapping between the lexical status of an item and the correct response to it is a simple direct one. Consequently, this could permit a response output to be triggered as soon as a continuous activation mechanism has reached threshold (McClelland, 1979; Ratcliff, 1978), without any elaborate discrete post-access processing. By contrast, the partial-information plateaus found in Experiments 2 and 3 may have been a product of discrete processes necessitated by the lexical-status comparisons and complex stimulus-response assignment used there. If our hypotheses are correct, then Experiment 5 may further illustrate the analytical power of speed-accuracy decomposition.

Method

Subjects. Four students from the same population as in Experiments 1 through 4 served as paid subjects. One of them (S.D.) had participated previously (see Experiment 1). The other three (P.C., D.P., and C.F.) were new.

Apparatus. The apparatus was the same as that used in Experiments 1 through 4.

Stimuli. Words and nonwords from Experiments 1 through 4 were again used. Each individual letter string served as a separate test stimulus. The word stimuli had relatively low frequencies as tabulated in the norms of Kucera and Francis (1967). This helped increase the variance of the regular-trial reaction time distributions, making it easier to position the onsets of the response signals relative to them.

Design. Following a series of practice sessions similar to those described earlier (see Method, Experiment 1), each subject participated in six test sessions. A test session included nine trial blocks, with 12 regular trials and 36 signal trials per block. For the signal trials, there were response signals with six different signal lags. Each lag occurred 6 times per block. We refer to the six response signals as s1, s2, . . . , s6, running from shortest to longest lag.

Procedure. The procedure was the same as in Experiments 1 through 4, except for changes made to implement the single-string lexical-decision task. Each test stimulus consisted of an individual word or nonword. Subjects were instructed to respond "yes" for the words and "no" for the nonwords. Positive responses required pressing a right-hand finger key, and negative responses required pressing a left-hand finger key.

Response-signal lags. An algorithm like those in Experiments 1 through 4 was used for adjusting the lags of the response signals. We positioned the signal with the longest lag (i.e., s6) such that, on the average, it induced guessing processes whose median completion time equaled approximately the 60th percentile of the reaction times obtained with word stimuli on regular trials. The signal with the shortest lag (s1) occurred 175 ms earlier than did the longest lag signal relative to the onsets of the test stimuli. The other intermediate signals (s2 through s5) had lags whose magnitudes were evenly spaced between those of the shortest lag and longest lag signals. This yielded a set of signal lags that averaged about 100, 135, 170, 205, 240, and 275 ms, respectively, for signals s1 through s6.

Data analyses. The data analyses were similar to those used in previous experiments.

Results

The main objective of Experiment 5 was to illustrate a new pattern of accumulated partial information associated with performing the single-string lexical-decision task. As before, this illustration requires examining results from the regular and signal trials. With the reaction times and accuracy levels obtained there, estimates of guessing-completion times and guessing accuracies may again be calculated by using Equations 2 and 4. These estimates then provide the basis for constructing a partial-information accumulation function.

Regular and signal trials. Some results from the regular and signal trials of Experiment 5 appear in Table 12. This table shows mean reaction times and response accuracy for each stimulus type (word and nonword) as a function of trial type and signal lag. During regular trials, incorrect responses were marginally faster (mean difference ≈ 40 ms) for words than for nonwords, F(1, 3) = 6.97, p < .1. However, correct responses were a bit slower (mean difference ≈ 13 ms) for words than for nonwords, F(1, 3) = 4.08, p = .14. Also, the accuracy level was significantly less (mean difference ≈ 3%) for words than for nonwords, F(1, 3) = 10.8, p < .05. These effects of lexical status differ from ones reported by some previous investigators (e.g., Meyer & Ruddy, 1973; Osman et al., 1986; Rubenstein et al., 1971). They may be attributed to our use of words that had relatively low frequencies. The low-frequency words were more difficult to discriminate from nonwords than is usually the case.

During signal trials, the effect of stimulus type on mean reaction times interacted marginally with signal lag: for correct responses, F(5, 15) = 2.47, p = .08; for incorrect responses, F(5, 15) = 2.52, p = .08. A reaction time difference between responses to words and nonwords was again present after long signal lags but not after short ones. As the signal lag decreased, mean reaction times decreased: for correct responses, F(5, 15) = 56.8, p < .001; for incorrect responses, F(5, 15) = 44.7, p < .001. Also, response accuracy decreased as signal lag decreased, F(5, 15) = 55.3, p < .001. At each signal lag, responses

Table 12

<table>
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<tr>
<th>Trial &amp; stimulus type</th>
<th>Correct responses</th>
<th>Incorrect responses</th>
<th>Response accuracy (% correct)</th>
</tr>
</thead>
<tbody>
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<td>Regular</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Word</td>
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<td>415</td>
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</tr>
<tr>
<td>Nonword</td>
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<td>Word</td>
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<td>358</td>
<td>68.9</td>
</tr>
<tr>
<td>Nonword</td>
<td>365</td>
<td>357</td>
<td>78.6</td>
</tr>
<tr>
<td>Signal4</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Word</td>
<td>386</td>
<td>376</td>
<td>73.7</td>
</tr>
<tr>
<td>Nonword</td>
<td>383</td>
<td>382</td>
<td>83.5</td>
</tr>
<tr>
<td>Signal5</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Word</td>
<td>405</td>
<td>401</td>
<td>79.9</td>
</tr>
<tr>
<td>Nonword</td>
<td>401</td>
<td>406</td>
<td>89.8</td>
</tr>
<tr>
<td>Signal6</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Word</td>
<td>427</td>
<td>421</td>
<td>86.1</td>
</tr>
<tr>
<td>Nonword</td>
<td>418</td>
<td>442</td>
<td>92.4</td>
</tr>
</tbody>
</table>

Note. Signal trials are subscripted in order of ascending signal lag.
Results Regarding the Guessing Processes
on Signal Trials in Experiment 5

Table 13

<table>
<thead>
<tr>
<th>Trial &amp; stimulus type</th>
<th>Completion time (milliseconds)</th>
<th>Duration (milliseconds)</th>
<th>Interquartile range (milliseconds)</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Signal, word</td>
<td>320</td>
<td>219</td>
<td>47</td>
<td>51.5</td>
</tr>
<tr>
<td>Nonword</td>
<td>324</td>
<td>224</td>
<td>55</td>
<td>70.6</td>
</tr>
<tr>
<td>Signal, nonword</td>
<td>341</td>
<td>205</td>
<td>63</td>
<td>55.2</td>
</tr>
<tr>
<td>Nonword</td>
<td>344</td>
<td>208</td>
<td>64</td>
<td>71.6</td>
</tr>
<tr>
<td>Signal, word</td>
<td>364</td>
<td>194</td>
<td>59</td>
<td>66.0</td>
</tr>
<tr>
<td>Nonword</td>
<td>372</td>
<td>201</td>
<td>68</td>
<td>72.3</td>
</tr>
<tr>
<td>Signal, nonword</td>
<td>390</td>
<td>185</td>
<td>67</td>
<td>69.0</td>
</tr>
<tr>
<td>Nonword</td>
<td>394</td>
<td>189</td>
<td>62</td>
<td>77.2</td>
</tr>
<tr>
<td>Signal, word</td>
<td>421</td>
<td>181</td>
<td>78</td>
<td>73.8</td>
</tr>
<tr>
<td>Nonword</td>
<td>432</td>
<td>191</td>
<td>79</td>
<td>82.2</td>
</tr>
<tr>
<td>Signal, nonword</td>
<td>470</td>
<td>194</td>
<td>94</td>
<td>80.2</td>
</tr>
<tr>
<td>Nonword</td>
<td>462</td>
<td>186</td>
<td>92</td>
<td>85.4</td>
</tr>
</tbody>
</table>

Note. Signal trials are subscripted in order of ascending signal lag.

to words were somewhat less accurate than responses to nonwords, \( F(1, 3) = 4.75, p = .11 \).

Guessing-completion times and durations. On the basis of these results, some inferences may be drawn about the nature of the guessing processes during signal trials of the single-string lexical-decision task. In particular, Table 13 shows estimates of guessing-completion times and guessing durations obtained with each response signal. These permit estimates of accumulated partial information to be plotted as a function of time, and they provide further tests of the assumptions made by the PSG model on which speed-accuracy decomposition rests.

Some of the results in Table 13 add credibility to the PSG model. Stimulus type (word vs. nonword) did not affect the mean guessing-completion times significantly (mean difference = 3 ms), \( F(1, 3) < 1.0, p > .50 \), and the effect of signal lag on those times did not interact significantly with stimulus type, \( F(5, 15) < 1.0, p > .5 \). The absence of an interaction supports the model’s temporal-independence assumption and is especially interesting given that signal lag and stimulus type did affect the observed signal-trial reaction times interactively (cf. Table 12). Also of interest are the facts that no significant stimulus-type effect, \( F(1, 3) < 1.0, p > .5 \), or stimulus-type by signal-lag interaction, \( F(5, 15) = 1.53, p > .20 \), occurred for the interquartile ranges of the guessing-completion times. Again this is consistent with the assumption of temporal independence between the guessing and normal processes of word recognition.

On the other hand, some aspects of the results in Table 13 do suggest possible deviations from perfect temporal independence. As the signal lag increased, the interquartile ranges of the guessing-completion times also increased significantly, \( F(5, 15) = 13.7, p < .001 \). This can be seen in the bottom panel of Figure 20, which shows Vincentized cumulative distributions of guessing-completion times as a function of signal lag. These distributions were obtained from the aforementioned regular-trial reaction times (Figure 20, top panel) and signal-trial reaction times (Figure 20, middle panel), using Equation 2. The distributions of guessing-completion times tended to fan out with increasing signal lag, exhibiting greater and greater variance, whereas strict adherence to the temporal-independence assumption would imply constant variance (cf. Figure 12).

How might the increasing variance of the guessing-completion times be explained? One possibility is that at longer signal lags, the guessing processes induced by the response signal actually interrupt normal recognition processes, rather than racing independently with them. If such interruption occurred with long-lag but not short-lag signals, it could yield an apparent increase in the variance of the estimated guessing-completion times as a function of signal lag. It would also cause the estimated duration of the guessing processes to increase as well.
(Footnote 14). However, we did not find the latter sort of increase. On the contrary, the mean guessing duration tended to decrease with increasing signal lag, $F(5, 15) = 11.0, p < .05$. So one must look elsewhere for an explanation of why the temporal-independence assumption was not entirely satisfied here. Given that other results from Experiment 5 were consistent with this assumption and that the PSG model has fit well during previous experiments, we will continue relying on it for now to estimate the accuracy of the guessing processes.

**Guessing accuracy.** Table 13 shows the estimated guessing accuracy as a function of signal lag. The mean accuracy of guesses was less for words than for nonwords, but this difference was not reliable across subjects, $F(1, 3) = 1.28, p > .3$. On the average, the guessing accuracy exceeded chance (i.e., 50%) regardless of stimulus type: for words, $F(1, 3) = 8.61, p < .1$; for nonwords, $F(1, 3) = 32.1, p < .01$. A linear trend accounted for more than 99% of the variance in mean guessing accuracy as a function of signal lag, suggesting that the relation between these two variables was reasonably smooth and monotonic.

The relation between guessing accuracy and signal lag is shown more clearly in Figure 21. Here we have plotted the mean accuracy of guesses (solid circles) made in response to words and nonwords versus the mean times at which the guesses were completed. Data obtained with each of the six response signals are included. It can be seen that each increment in signal lag yielded a small or moderate increase in guessing accuracy. Also marked in Figure 21 is the minimum regular-trial reaction time associated with the Vincentized reaction time distribution for word stimuli on regular trials, which reflects the completion times of the fastest normal recognition processes. This benchmark indicates that the guessing accuracy increased steadily throughout much of the time period during which the normal processes were being completed.

**Guessing sensitivity and bias.** A signal-detection analysis confirms that these changes in guessing accuracy as a function of signal lag came from increased guessing sensitivity.29 The results of this analysis appear in Table 14, which shows guessing sensitivity ($d'$) and bias (log $\beta$) separately for each subject and stimulus type: for words, $F(5, 15) = 27.9, p < .001$. A linear trend accounted for more than 98% of the variance in mean $d'$. The other two subjects (D.P. and C.F.) produced perfectly monotonic increases of $d'$.

The subjects did exhibit some idiosyncratic differences in response bias. For three of them (S.D., P.C., and D.P.), the value of log $\beta$ was consistently positive ($p < .05$ in each case), indicating a bias toward negative responses when the guessing processes finished ahead of the normal recognition processes. However, the other subject (C.F.) exhibited consistently negative values of log $\beta$ ($p < .05$), indicating a bias toward positive responses. Signal lag did not affect these biases in any systematic fashion.

**Comparison with normal sensitivity.** Also shown in Table 14 are the estimated sensitivity and bias of the completed normal processes on regular trials. As before, these processes had greater sensitivity than did the corresponding guessing processes (cf. Tables 4, 7, and 10). Even when the signal lag was relatively long, this difference still persisted, $F(1, 3) = 82.4, p < .01$. Nevertheless, the guessing processes did come closer to the level of performance associated with the normal processes during Experiment 5 than during previous experiments. For example, the sensitivity of guesses induced here by the longest lag signal (i.e., $s_5$) reached about 54% of the normal sensitivity on regular trials (mean $d' = 1.98$ vs. 3.66). In contrast, the guessing sensitivity never exceeded 40% of the normal sensitivity under the conditions of Experiment 3.

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29 In this analysis, the probabilities of positive (i.e., correct) guesses for words served as hit rates, and the probabilities of positive (i.e., incorrect) guesses for nonwords served as false-alarm rates (cf. Footnotes 22 and 23).
Discussion

The results of Experiment 5 provide an instructive complement and contrast to those of our previous studies (cf. Experiments 1 through 4). During Experiment 5, subjects performed a single-string lexical-decision task in which they made decisions about individual words and nonwords. The required processing of test stimuli and mapping of decisions onto responses were relatively simple here, whereas they were more complex for the prior dual-string lexical-decision task. This change of task yielded a new pattern of accumulated partial information. Unlike before, the partial-information accumulation function increased steadily as the signal lag and guessing-completion times increased. The accumulated partial information did not appear to level off at an intermediate plateau, even though the longer signal lags induced guesses that finished relatively late compared with the typical completion times of the normal recognition processes. So on the basis of Experiment 5, we have achieved our goal of demonstrating that speed-accuracy decomposition can reveal a variety of different information-processing characteristics.

To get a precise overview of the differences between the results of Experiment 5 and those of Experiments 1 through 4, one may simply compare Figures 16 and 21. Figure 16 shows the intermediate partial-information plateau associated with performing the dual-string lexical-decision task. From such data, one might be tempted to claim that subjects' performance incorporated a set of discrete processes, as suggested previously (see Discussion, Experiment 3). The partial-information plateau could stem from quantized comparisons between the lexical-status values of different letter strings. On the other hand, Figure 21 shows a steady accumulation of partial information associated with performing the single-string lexical-decision task. From such data, one might claim that performance involved a gradual activation of recognition and decision processes. The latter pattern is consistent with continuous deterministic models of word recognition, including the cascade model (McClelland, 1979) and the interactive-activation model (McClelland & Rumelhart, 1981). Following our outline of the performance requirements imposed by the single-string lexical-decision task, these models seem like reasonable ones to account for the results of Experi-
ment 5, in which the stimulus-response assignment was less complex than before.

General Discussion

The introduction to this article outlined several inherent limitations of conventional reaction time and speed-accuracy trade-off procedures. Data from these procedures reflect only the total duration and overall accuracy associated with a complex system of mental processes. They do not provide detailed insights into the intermediate products of rapid information processing. To help solve this problem, we have developed the PSG model and speed-accuracy decomposition technique. The PSG model incorporates hypothesized normal and guessing processes that, in various combinations, may contribute to subjects' performance of cognitive tasks where there is a hybrid mixture of regular reaction time trials and peremptory response-signal trials (TRT procedure). A componential analysis of reaction time and accuracy data based on the PSG model yields new and instructive estimates of the partial information that subjects accumulate over time before responding to a given test stimulus. Obtained partial-information accumulation functions can be used for testing predictions made by discrete and continuous models of information processing.

To illustrate the utility of the PSG model and speed-accuracy decomposition technique, we have reported five representative experiments. The experiments required subjects to use word recognition and comparison processes that, depending on one's theoretical predilections, might be expected to entail discrete or continuous outputs of partial information (McClelland & Rumelhart, 1981; Meyer et al., 1974, 1975; Rubenstein et al., 1971). During Experiments 1 through 4, performance involved a dual-string lexical-decision task. Subjects there made positive and negative judgments about whether paired strings of letters had the same lexical status (cf. Meyer & Schvaneveldt, 1971). This task was chosen because it calls for a comparison of binary lexical-status values, embodies a complex stimulus-response assignment, and imposes high demands on recognition capacity, which could lead to a discrete-processing strategy. In contrast, performance during Experiment 5 involved a single-string lexical-decision task in which subjects made yes–no lexical (word–nonword) decisions about individual letter strings. The stimulus–response assignment and capacity demands there were sufficiently modest that a simple continuous-processing strategy could perhaps accommodate them.

The present experiments have achieved most of our objectives. Several informative findings emerged from them. These findings bear not only on the PSG model and the speed-accuracy decomposition technique but also on the nature of word recognition and other associated mental processes.

Summary of Findings

The major findings of Experiments 1 through 5 may be summarized with respect to three basic questions: (a) Do equivalent normal processes of word recognition and lexical-status comparison underlie performance in conventional reaction time procedures and in the TRT procedure, in which regular and signal trials are mixed randomly? (b) Are the technical assumptions of the PSG model valid? (c) Can speed-accuracy decomposition reveal different interpretable patterns of accumulated partial information as a function of task demands, even though such differences are not apparent from conventional speed-accuracy tradeoff curves? As we have argued, the answer to each of these questions is at least a tentative "yes."

Equivalence of normal processes. The strongest evidence of normal-process equivalence was found in Experiment 4. When we compared performance on regular (nonsignal) trials of pure and mixed blocks, it appeared that mixing signal trials with the regular trials had rather limited effects. Regular trials of the mixed blocks yielded somewhat shorter reaction times and a bit higher error rates (Table 11), but the effects of key independent variables such as stimulus type and word frequency remained about the same regardless of block type (Figures 17 and 18). There was no indication that the TRT procedure qualitatively altered the central components of word recognition and lexical-status comparison. Thus, we conclude that the present results, and the inferences derived from them, may generalize beyond the present context.

Validity of the PSG model. We made repeated efforts to test several important assumptions of the PSG model during all of our experiments. The experiments focused especially on the model's temporal independence, winner-takes-all, and full-access assumptions. By and large, each of these assumptions seems reasonably consistent with the obtained results.

Two general sorts of observations support the temporal-independence assumption. First, we found that guessing-completion times were usually about the same regardless of the stimuli being processed, even though stimulus type markedly affected regular-trial reaction times. Second, the shapes of the distributions of guessing-completion times remained at least roughly invariant with changes in the response-signal lag. The major signal-lag effect was to shift the mean guessing-completion times by about the same amounts as the objective differences between the lengths of the lags. Similarly, the durations of the guessing processes were not affected much by either stimulus type or signal lag. Within the context of the PSG model and Equation 2, such results could not have occurred if the guessing and normal processes deviated greatly from perfect temporal independence.

The full-access assumption of the PSG model is likewise supported at least indirectly. In each of our experiments, all subjects had some useful partial information after sufficiently long response-signal lags. Performance during both the single-string and dual-string lexical-decision tasks benefited from this information. The primary effect of switching tasks was to change the form of the partial-information accumulation function. If subjects had not been reasonably thorough at exploiting available partial information during the course of normal processing, then it is unlikely that we could have detected such changes so easily.

Patterns of accumulated partial information. Given the results of Experiments 1 through 5, there is now little doubt that speed-accuracy decomposition can reveal different interpretable patterns of accumulated partial information, depending on the cognitive task that subjects have to perform. Two distinct patterns have been derived so far with the decomposition technique. For the dual-string lexical-decision task (Experiments 1
through 4), the partial-information accumulation function exhibited a stable intermediate plateau (e.g., see Figure 16). For the single-string lexical-decision task (Experiment 5), on the other hand, the partial-information accumulation function increased steadily throughout the time range in which the normal recognition processes were being completed (Figure 21). These patterns accord with differences between the logical requirements of the two alternative lexical-decision tasks. Speed-accuracy decomposition therefore offers some promise as a future diagnostic indicator of task performance across various cognitive domains.

**Hybrid Model of Word Recognition and Comparison**

The partial-information accumulation functions revealed here pose an intriguing theoretical picture with respect to the alternative classes of information-processing models outlined earlier (Table 1). We assume that lexical decisions about individual strings of letters must take place as part of performing the dual-string lexical-decision task. However, the accumulated partial information in the dual-string lexical-decision task had an intermediate plateau (Figure 16), whereas there was a steady increase of partial information in the single-string lexical-decision task (Figure 21). Looking back at Table 1, it appears that no one processing model can easily accommodate this pattern. Consequently, one might propose a hybrid model, with a combination of both discrete and continuous components, to characterize the normal processes of word recognition and lexical-status comparison.

For example, consider Figure 22. Here we have depicted a hypothetical processing system for performance of the dual-string (same–different) lexical-decision task (cf. Meyer & Schvaneveldt, 1971). According to this view, performance begins with component processes that encode the letter strings of a pair and then identify the lexical status of each string. The identification process involves accessing information about words stored in long-term lexical memory. It produces a binary output for each string, indicating that the string is either a word or nonword. Next there is a process that compares the lexical status of one string with the lexical status of the other. If the status values of the two strings match, then the comparison process produces a positive output; otherwise, the output is negative. For reasons discussed later, the output of the comparison process may be either tentative or definitive. A definitive output leads directly to the execution of a corresponding positive or negative response. A tentative output leads to a subsequent verification process, which rechecks the identification process for an update on the lexical status of each letter string and then repeats the comparison process once more. When it is needed, the verification process produces the definitive output that determines the system’s ultimate response.

On the basis of results from the single-string lexical-decision task (Experiment 5), it is reasonable to claim that the encoding and identification of individual letter strings are continuous processes, as proposed under the cascade and interactive-activation models (McClelland, 1979; McClelland & Rumelhart, 1981). This would account for the monotonic accumulation of partial information when subjects make lexical decisions about letter strings in Experiment 5. We suggest, however, that the subsequent comparison and verification processes needed for dual-string (i.e., same–different) lexical decisions are discrete. This would account for the results of Experiments 1 through 4, which revealed an intermediate partial-information plateau. The plateau may arise from occasions on which the initial comparison process produces a tentative output and further verification is performed before response execution. Tentative positive and negative outputs by the comparison process could provide a basis for constant better-than-chance guessing accuracy over a period of time before the verification process has produced a definitive output.

Under this hybrid model, several other details should be noted as well. Prompted guesses in the single-string lexical-decision task could directly use whatever information has been accumulated by the encoding and identification processes about the lexical status of an individual letter string, because the products of those processes would require no extra transformations to meet the demands of the task. Yet such products would not contribute directly to the estimated accuracy of prompted guesses in the dual-string lexical-decision task, because by themselves they provide no basis for correctly judging whether two strings of letters have the same lexical status.

Furthermore, definitive positive and negative outputs by the initial comparison process would not contribute to estimated guessing accuracy in the dual-string lexical-decision task. They are assumed to exit the system immediately without any subsequent verification and so would be removed from guessing-accuracy estimates through speed-accuracy decomposition (Equation 4). The apparent effects of these outputs could emerge on regular trials in which the responses are relatively
fast. For example, minimum regular-trial reaction times may reflect responses executed immediately on the basis of definitive outputs by the initial comparison process (cf. Kounios et al., 1987). This may explain why such times are not much, if any, greater than the times at which above-chance guesses are first completed after the onsets of test stimuli in the dual-string lexical-decision task.

Why are the positive and negative outputs by the initial comparison process sometimes tentative rather than definitive, and why is there a subsequent verification process for checking them? The answers to these questions may stem from the combination of discrete and continuous processes we have hypothesized. During performance of the dual-string lexical-decision task, the continuous identification process could accumulate information about the lexical status of letter strings at different rates on different trials (cf. Ratcliff, 1988). To take advantage of occasions on which the accumulation rate is relatively high, the system may transmit the current status of the identification process to the initial comparison process at a preset time after test-stimulus onset, but the identification process may continue onward while the initial comparison process is underway. The reliability of the inputs to the initial comparison process would then fluctuate from trial to trial. When this input reliability is high because the identification process happens to have a high information-accumulation rate, the initial comparison process could generate definitive positive or negative outputs for response execution without further deliberation. Tentative outputs could constitute the system’s attempt to guard against spurious errors when the reliability of inputs to the initial comparison process is low. By rechecking the identification process at a later time, the system may evaluate a prospective course of action before executing it.

Our hybrid model for dual-string lexical decisions has some features in common with models developed by previous investigators. For example, Atkinson and Juola (1973) have proposed an initial continuous decision process and a final discrete verification process to explain data concerning episodic recognition memory of “old” test words versus “new” distractor words. According to their account, the initial-decision process is based on a preliminary assessment of stimulus familiarity (strength of “oldness”). If this assessment yields a familiarity value above a preset positive threshold, then a positive response occurs immediately; if it yields a value below a preset negative threshold, then a negative response occurs immediately. Otherwise, when the stimulus familiarity falls within a middle range, the verification process initiates a discrete serial search of episodic memory to determine whether the stimulus exists among items stored there. On the basis of this search, a positive or negative response ultimately occurs as a result of either a match with some stored item or mismatches with all items. These proposed decision and verification processes together fit numerous aspects of Atkinson and Juola’s (1973) data, including effects of memory-set size and stimulus repetition on reaction times and error rates.

Analogous models with discrete comparison and verification processes have also been applied in a number of other domains. Such applications range from studies of same–different letter matching (Bamber, 1972) to investigations of word recognition (Becker, 1980; Meyer & Ruddy, 1973; Rubenstein et al., 1971) and sentence comprehension (Meyer, 1970, 1973, 1975; Rips, 1975; E. E. Smith et al., 1974). The present hybrid model therefore has considerable historical precedent.

**Implications for Continuous Models**

Although we have proposed some discrete component processes to account for results from the dual-string lexical-decision task, one still might wonder whether any continuous models can explain those results equally well. As mentioned previously, a stochastic diffusion model (Ratcliff, 1978, 1988) predicts a partial-information plateau that mimics our findings in Experiments 2 and 3 (cf. Table 1). This prediction assumes that response strength is a random variable whose magnitude drifts stochastically over time, producing a Gaussian distribution of intermediate partial-information states after the onset of a test stimulus. It also assumes that as time passes, the distribution of partial-information states becomes conditioned to include only cases in which response strength has remained relatively low and not yet crossed a fixed strength threshold (cf. Figures 3 and 8). Given these assumptions, the stochastic diffusion model may yield a virtually constant intermediate level of guessing accuracy like subjects exhibit in response to paired letter strings on signal trials with medium to long signal lags. Nevertheless, there are certain reasons to question the validity of such an alternative account.

Some persisting doubts about the stochastic diffusion model stem from details of the results obtained in Experiments 1 and 3. If this model were valid, then one might expect partial information to be available over a significant period of time before the normal processes involved in response-strength drift have reached threshold (Figure 3). It is such availability that, in part, allows the stochastic diffusion model to emulate typical speed–accuracy trade-offs (Ratcliff, 1978). However, in the dual-string lexical-decision task, there was a rather lengthy dormant period during which guessing processes had essentially no partial information available to them from concurrent normal processes. We failed to observe better-than-chance guesses even when the guessing processes were completed almost 500 ms after the onsets of the test stimuli (see Results, Experiment 1). Just 50 ms or so later than those guessing-completion times, the fastest normal processes, which had high information and produced very accurate responses ($P_e(\text{correct}) = .95$), were completed.

These findings strain the credibility of the stochastic diffusion model. The strain seems especially great if some other plausible ancillary assumptions are made as well about relations between the observed regular-trial reaction times and the estimated guessing-completion times. For example, let us suppose that the stochastic diffusion model is valid and that the following relations hold.

1. The reaction times on regular trials, which represent the durations of completed normal processes, are a sum of five components, including the time taken to encode the test stimulus, the time taken for response strength to drift from its initial base level to a preset threshold, the time taken to make a decision after reaching the threshold, the time taken to select a response in terms of that decision, and the time taken to execute the response.

2. The completion times of the guessing processes estimated...
through speed-accuracy decomposition on signal trials are also a sum of five component durations, including the lag (i.e., SOA) of the response signal, the time taken to detect the signal and access the current level of response strength, the time taken to make a decision based on the accessed response strength, the time taken to select a response in terms of that decision, and the time taken to execute the response.

3. In combination, the decision, response selection, and response execution components associated with the regular-trial reaction times take at least as long do the corresponding components associated with the guessing-completion times.\(^{30}\)

Given these three assumptions, an interesting implication emerges. The time from when the response strength (i.e., partial information) is accessed by the guessing processes until when the strength threshold is crossed by the normal processes must be less than or equal to the difference between the regular-trial reaction times and guessing-completion times.\(^{31}\) Thus, to accommodate the high accuracy of the fastest normal processes (i.e., those with minimum regular-trial reaction times), which finish immediately after the dormant period of extremely low guessing accuracy, the stochastic diffusion model must incorporate a large and very rapid rise in response strength, whose onset occurs at about the same time as the fastest normal processes reach their final high information level.\(^{32}\)

This requirement compromises the true spirit of continuous models. It entails an essentially quantum jump in available information, like those embodied by the step functions of Figure 5 (bottom panel) and Figure 6 (top panel). If the stochastic diffusion model and other continuous models must incorporate a "rapid-rise" feature to account for reaction time and accuracy data, then little would remain to distinguish them empirically or theoretically from competing discrete models (Meyer, Yantis, Osman, & Smith, 1985). An important goal for future research should therefore be to obtain additional data through speed-accuracy decomposition regarding the true rates of continuous information accumulation.

**Limitations of Speed-Accuracy Decomposition**

Of course, we do not wish to leave an impression that speed-accuracy decomposition cures all of the weaknesses that beset conventional reaction time procedures and speed-accuracy trade-off methodology. The decomposition technique helps reveal more details regarding the intermediate products of rapid mental processes, but it has some significant limitations. To warn readers about these limitations, so that failed attempts at measuring and interpreting partial-information accumulation functions will not occur in the future, we mention a few potential pitfalls.

1. For coping with the hybrid mixture of regular and signal trials on which speed-accuracy decomposition relies, subjects should have considerable practice. Subjects cannot ordinarily master the TRT procedure and produce reliable data in a single test session. Practice is necessary to achieve temporal independence between the normal and guessing processes assumed by the PSG model (cf. Hirsh et al., 1980; Schneider & Shiffrin, 1977). Experimenters who adopt the decomposition technique must be prepared to test small numbers of subjects intensively, following a regimen of the sort commonly used by psychophysicists (Green & Swets, 1966).

2. Not all subjects and not all types of tasks will necessarily yield results consistent with the assumptions of the PSG model. We have found occasional individuals who, despite extensive practice, still violate the requirements of the TRT procedure. These individuals may fall at the extremes of personality dimensions such as impulsivity–reflectivity (Dickman & Meyer, 1988). Similarly, some cognitive tasks may be less amenable than others to satisfying the PSG model’s assumptions. It is therefore important to test these assumptions thoroughly before extracting partial-information accumulation functions.

3. The theoretical interpretation of these functions calls for careful thought. As we have illustrated already in our treatment of discrete stage models versus the stochastic diffusion model, a particular pattern of accumulated partial information (e.g., step function with an intermediate plateau) may be open to multiple accounts (cf. Ratcliff, 1988). Noise associated with inherent processing variability can, in some cases, obscure the true shape of an underlying partial-information accumulation function, just as it does with ordinary speed-accuracy trade-off curves (Figure 5). For example, if there are large fluctuations in the times at which transitions take place between discrete states of no information and constant intermediate partial information, then this could prevent the discovery of a partial-information plateau even with speed-accuracy decomposition.

Future research with the decomposition technique will be necessary to assess the extent of these limitations and to evolve further ways of circumventing them.

**Other Directions for Future Research**

There are a number of other promising directions for future research with the speed-accuracy decomposition technique

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\(^{30}\) This third assumption is especially plausible in light of the extra time pressure imposed by the response signals on signal trials.

\(^{31}\) The basis of this implication is straightforward. Let the regular-trial reaction times and the guessing-completion times be denoted by \(t_r\) and \(t_g\), respectively. Then according to Assumption 1, \(t_r = t_1 + t_2 + t_3 + t_4 + t_5\), where the components on the right side of this equation represent the respective durations of encoding, response-strength drift, decision, response selection, and response execution. Similarly, from Assumption 2, \(t_g = \text{SOA} + t_1 + t_2 + t_3 + t_4 + t_5\), where the components on the right side of this equation represent the respective durations of signal lag, signal detection and response-strength access, decision, response selection, and response execution. Now by definition, \(t_5 = \delta_g + \epsilon_g\), where \(\delta_g\) is the amount of time from when the response-strength drift starts until it is accessed by the guessing processes, and \(\epsilon_g\) is the remaining time until the drift process reaches threshold. Also, by definition, \(\text{SOA} + t_1 + t_2 + t_3 + t_4 + t_5\), as required by Assumption 3, then \(\epsilon_g \leq t_r - t_g\), which is the stated implication.

\(^{32}\) For example, consider the results of Experiment 1. There the guessing processes induced by the short-lag response signal did not exceed chance significantly, even though the completed normal processes were very accurate. Also, the completion times of the fastest normal processes were only about 50 ms greater than the mean guessing-completion times obtained with the short signal lag. So within this amount of time (i.e., 50 ms) or less, the response strength that mediated the fastest accurate guesses significantly, even though the completed normal processes were very accurate. Also, the completion times of the fastest normal processes were only about 50 ms greater than the mean guessing-completion times obtained with the short signal lag. So within this amount of time (i.e., 50 ms) or less, the response strength that mediated the fastest normal processes must have drifted from its base level to a much higher threshold level.
Partial-information accumulation functions (guessing sensitivity $[d']$ vs. guessing-completion time [GT]) from an experiment on semantic-memory retrieval and sentence comprehension by Kounios, Osman, and Meyer (1987). (The open squares represent results for discriminations between sentences whose categories had disjoint and subset relations. The solid diamonds represent results for discriminations between sentences whose categories had superset and subset relations.)

**Figure 23.** Partial-information accumulation functions (guessing sensitivity $[d']$ vs. guessing-completion time [GT]) from an experiment on semantic-memory retrieval and sentence comprehension by Kounios, Osman, and Meyer (1987). (The open squares represent results for discriminations between sentences whose categories had disjoint and subset relations. The solid diamonds represent results for discriminations between sentences whose categories had superset and subset relations.)

and TRT procedure. In closing, we mention two of these briefly. One involves supplementing measures of accumulated partial information with additional dependent variables derived from psychophysiological recording methods. A second involves applying the decomposition technique to analyze performance of complex cognitive tasks beyond the domain of word recognition.

**Psychophysiological recording methods.** Some dependent variables derived from psychophysiological recording methods may significantly strengthen inferences based on speed-accuracy decomposition. The decomposition technique is intended to provide detailed evidence about the products of rapid mental processes. A principal focus of the technique is the partial-information accumulation function, which reflects the intermediate outputs of discrete and continuous mental processes that increase response accuracy over time. Although this function offers new insights into information-processing dynamics, it by no means tells the whole story. Specific patterns of accumulated partial information may still remain open to multiple theoretical interpretations (e.g., Table 1). The residual ambiguity could perhaps be resolved by taking other diagnostic indicators into account.

Psychophysiological recording methods have dealt with two different sorts of dependent variables that seem especially appropriate for this endeavor: cortical event-related potentials (ERPs) and electromyographic (EMG) activity. ERPs are voltages recorded from the scalp, reflecting patterns of neural events in the brain during the performance of various cognitive tasks. They include a number of specific components (e.g., N200, P300, N400, and readiness potential) that are, in theory, associated with particular mental processes (Donchin, 1979; Gaillard & Ritter, 1983). Some investigators have claimed, for example, that the P300 component, a positive voltage peak manifested around 300 ms after the onset of a test stimulus, may stem from a stimulus-evaluation or memory-updating process triggered by various features of the stimulus (Coles et al., 1985; Karis, Fabiani, & Donchin, 1984). Analogously, EMG activity, which occurs at the interface between motor neurons and muscle tissue (Loeb & Gans, 1986), may reflect subsequent peripheral response processes associated with the preparation and execution of physical movements.

An interesting study that illustrates the potential power of such measures for analyzing the dynamics of information processing has been reported by Coles et al. (1985). They had subjects identify selected target letters in arrays of flanking distractor letters. Visual similarity among the target and distractor letters was manipulated systematically. Several dependent measures of performance, including reaction time, response accuracy, ERPs (e.g., P300), and EMG activity were recorded. Observed correlations between the independent and dependent variables, together with partial correlations between the dependent variables, led Coles et al. (1985) to argue that letter-identification entails a continuous flow of information from stimulus input to response output (cf. Eriksen & Schultz, 1979). For example, when the distractor letters were visually similar to the target letters, a gradual growth of EMG activity was observed in muscles that, if fully activated, would have produced an incorrect manual response. Such activity occurred even when subjects eventually made the correct responses. Analogous results have also been obtained through differential measures of the readiness potential in the motor cortex during performance of the letter-identification task (Coles & Gratton, 1986).

It would be interesting to combine batteries of psychophysiological measures with partial-information accumulation functions derived from speed-accuracy decomposition. Under conditions in which partial information accumulates gradually over time, one might anticipate a corresponding gradual increase in the readiness potential and EMG activity, mediated by underlying continuous processes. In contrast, the absence of an intermediate readiness potential and EMG activity could, if coupled with chance guessing accuracy or a partial-information plateau, add credibility to discrete models of information processing (cf. Coles et al., 1985). So from examining such correlations, further guidelines may emerge for drawing inferences based on psychophysiological measures as well as on partial-information accumulation functions.

**Application to complex cognitive tasks.** It would also be interesting to use the speed-accuracy decomposition technique in analyzing performance of various complex cognitive tasks. Although we have used the decomposition technique primarily for analyzing word recognition, this is not its only possible application. Mental processes associated with sentence comprehension, visual imagery, reasoning, and problem solving may also be understood better in terms of partial-information accumulation functions like those reported here.

An illustration of such possibilities appears in a study by Kounios et al. (1987). They asked subjects to judge the truth of universal-affirmative sentences about natural semantic categories (e.g., "All collies are dogs," "All flowers are roses," and "All
chairs are foods") that had subset, superset, and disjoint relations. The judgments were made in the context of the TRT procedure with mixed regular and signal trials. Performance (i.e., reaction time and response accuracy) was measured as a function of signal lag and the set relations between the subject and predicate categories of the sentences. Through speed-accuracy decomposition, estimates of accumulated partial information were obtained for discriminations between sentences with disjoint and subset relations, and for discriminations between sentences with superset and subset relations.

The objective of Kounios et al.'s (1987) study was to test alternative models of semantic-memory retrieval and sentence verification. According to one popular model, for example, these processes involve sequentially comparing the semantic features of the subject and predicate categories in a sentence (McCloskey & Glucksberg, 1979; Meyer, 1970; E. E. Smith et al., 1974). Such comparisons would yield gradually accumulating information about whether the sentence is true or false, on the basis of how many and what kind of feature matches are found. So the semantic feature-comparison model implies that the partial-information accumulation function obtained through speed-accuracy decomposition of performance in the sentence-verification task should increase steadily over time. In contrast, other models (e.g., ones involving a simple all-or-none network) predict that performance of the dual-string lexical-decision task (Experiments 1 through 4) should increase steadily over time. In contrast, other models (e.g., ones involving a simple all-or-none network) predict that performance of the dual-string lexical-decision task (Experiments 1 through 4) should increase steadily over time.

Thus, by measuring accumulated partial information, Kounios et al. (1987) were able to assess the nature of retrieval and verification processes.

Figure 23 shows some results that Kounios et al. (1987) obtained through speed-accuracy decomposition. Here, estimates of guessing sensitivity (d') have been plotted versus mean guessing-completion times for two types of discriminations between sentences: disjoint versus subset (open squares) and superset versus subset (solid diamonds). In each case, the guessing sensitivity tended to increase monotonically as the guessing-completion time increased. There was no evidence of chance guessing or a partial-information plateau as we would observe if subjects' performance of the dual-string lexical-decision task (Experiments 1 through 4). However, the rate of increase in guessing sensitivity during sentence verification did depend systematically on the type of discrimination involved. A higher rate (i.e., steeper slope) occurred when subjects discriminated disjoint sentences (e.g., "All chairs are dogs") from subset sentences (e.g., "All collies are dogs") than when they discriminated superset sentences (e.g., "All flowers are roses") from subset sentences. This is consistent with the semantic feature-comparison model outlined earlier, and it provides another example of how speed-accuracy decomposition offers useful insights into task performance.

**Taxonomy of cognitive tasks.** Through studies like the present ones and those of Kounios et al. (1987), it may ultimately be possible to construct a comprehensive taxonomy of various cognitive tasks. The taxonomy should specify the form of the partial-information accumulation function underlying the performance of each task. With this specification in hand, one would then have a firmer foundation on which to interpret reaction time and accuracy data from different domains and to make inferences about the dynamics of cognition and action.

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**Call for Nominations for Editor of Behavioral Neuroscience**

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