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Isolating the interference caused by cue duration in partial report: A quantitative approach

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In bar-probe partial report experiments, subjects are presented with a brief array of letters, followed by a cue that singles out a target letter. Using this procedure, V. M. Townsend (1973) reported a counterintuitive effect: As the duration of a cue was increased, target performance decreased dramatically. The aim of the present study was to isolate the locus of the cue-duration effect. To this end, several characteristics of the bar-probe display were manipulated in a single experiment: the interstimulus interval between the array and the cue, array density, the number of letters, and the number of symbols adjacent to the target. These factors were manipulated on a priori grounds so as to affect the different sources of information used in the bar-probe task—namely, durable storage, abstract identity information, and feature level information. The data were accurately fit by a simple quantitative, multinomial model that assumes that the different sources of information used in the bar-probe task make independent contributions to performance. The critical assumption of the model is that cue duration interferes with only one source of information—namely, feature level information.

In the present research, we investigated the effect of cue duration in partial report. In the partial report task, subjects are shown an array of items briefly, followed by a cue that indicates a portion of the array to be reported (see, e.g., Sperling, 1960). In the version of this task with which we are concerned, subjects are cued to report a single item by a bar pointing to a position in the array (see, e.g., Averbach & Coriell, 1961). Partial report performance is commonly held to index the rapid loss of labile visual information accrued from the brief display (see, e.g., Coltheart, 1980). However, V. M. Townsend (1973) reported a counterintuitive result that seems to be inconsistent with this simple interpretation: Performance was worse with long-duration cues than with short-duration cues. This detrimental effect of cue duration is substantial and has been replicated numerous times (e.g., Dixon & Di Lollo, 1991, 1994; Dixon, Gordon, Leung, & Di Lollo, 1997). We present here a quantitative analysis of partial report performance that isolates the cue-duration effect to the use of rapidly decaying information concerning visual features, as distinct from abstract identity codes or verbal information.

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Sources of Information Used in Partial Report

Our analysis follows from the common theoretical assumption that performance in partial report tasks reflects the contribution of multiple sources of information (see, e.g., Coltheart, 1980; Dixon & Di Lollo, 1991, 1994; Irwin & Yeomans, 1986; Mewhort, Campbell, Marchetti, & Campbell, 1981; Sperling, 1960). Early theoretical analyses presumed that performance depended on two sources of information: a stable but incomplete store of information and a more labile but comprehensive store. On this analysis, the stable information is related to the level of performance that occurs when subjects attempt to recall all of the items in the array (i.e., the so-called *whole report* performance), whereas the labile form corresponds to the information that is lost quickly after the offset of the array. Subsequent research has provided evidence on the nature of the stable and labile components.

Initially, the stable store of information was identified with the contents of verbal short-term memory (see, e.g., Sperling, 1967), but there are good reasons to suspect that this notion is not completely correct. For example, in whole report from briefly presented arrays, performance declines only slightly when subjects must simultaneously maintain a set of verbal items (Scarborough, 1972), and the patterns of errors reflect visual display factors rather than verbal confusions (Wolford, 1975). Similarly, partial report performance at long delays should reflect primarily the contribution of the stable component. However, such performance is only minimally affected by articulatory suppression (see, e.g., Dixon & Shedden, 1993), suggesting that the stable component is not based solely on articulatory or phonological codes. Thus, it seems likely that a substantial portion of the stable information in partial report is composed of some form of nonverbal information, even though it is likely to be distinct from the rapidly lost information about visual form. We suspect that this information is more abstract than visual feature information and is similar to verbal codes, in that it indicates the identity of items in the display. We refer to this information as *abstract identity codes*.

The notion that abstract identity codes contribute to partial report performance is not a new one. For example, Mewhort et al. (1981) incorporated identity codes into their dual-buffer model of performance in the bar-probe task. In their model, information in a precategorical feature buffer is processed and transformed into abstract identity codes that are stored in a character buffer. A similar idea was proposed by Irwin and Yeomans (1986). The main difference between the model of Mewhort et al. and that of Irwin and Yeomans is in the role of the partial report probe. Mewhort et al. proposed that the probe is used by an attentional mechanism to select information for transfer from the character buffer to durable storage. Irwin and Yeomans, on the other hand, hypothesized that the probe first directs translation from feature information to abstract identity information and then guides the transfer of information into durable storage. Nevertheless, both models share two assumptions concerning the nature of the mental representations. The first is that abstract identity codes represent a relatively stable source of nonverbal information. Thus, there should be relatively little loss of abstract identity information with increasing cue delay. The second assumption is that the location information associated with abstract identity codes is relatively coarse or impoverished. This accounts for the common finding that the ability to locate items in the visual field declines markedly with an increasing interstimulus interval (ISI), even though the ability to report on item identities does not (e.g., V. M. Townsend, 1973). Presumably, performance at short delays reflects the contribution of more precisely located information about visual form.

The other major source of information used in partial report could be construed as labile feature information. Traditionally, this type of information is assumed to be precategorical in nature. Moreover, it is often assumed that this information decays soon after the offset of the display (see, e.g., Irwin & Yeomans, 1986). However, a variety of research has identified not one, but two kinds of decay that affect performance. First, features may simply be lost over time, and as a consequence, identification of the corresponding visual form would have to based on incomplete information. Second, visual features may *drift* and be incorrectly combined with features from other locations (see, e.g., Irwin & Yeomans, 1986; Wolford, 1975; cf. Treisman & Schmidt, 1982). These mechanisms provide a basis for explaining the contribution of perceptual factors to partial report performance. For example, when the stimulus onset asynchrony (SOA) between a partial report display and a subsequent pattern mask is increased, accuracy improves, and intrusion errors decrease (Mewhort et al., 1981). Presumably, the increased display-mask SOA allows more accurate identification of visual feature information. Similarly, both intrusion and transposition errors decline with increasing spacing between the target and adjacent items (see, e.g., Irwin, 1992); it seems likely that the increased spacing reduces the likelihood of features drifting and combining incorrectly with the information at other locations.

A Unifying Framework for Models of Partial Report

Following from our analysis of the literature, it seems reasonable to assume that verbal, abstract identity, and labile feature information are major contributors to performance in partial report. Building on this assumption, we construct a simple conceptual framework for describing partial report performance. We refer to this framework as the tripartite framework of partial report. The framework provides a foundation for our quantitative analysis of the effect of cue duration. In the following paragraphs, we provide a more detailed description of this approach.

The tripartite framework follows from the work of Di Lollo and Dixon (1988; Dixon & Di Lollo, 1991). Di Lollo and Dixon assume, as do we, that partial report performance is based on multiple sources of information. In their terms, performance is based on visible persistence, visual analog representation (or schematic persistence; Dixon & Di Lollo, 1991), and durable storage. In our terms, these sources of information represent labile feature information, abstract identity information, and verbal information, respectively. Regardless of the labels used to identify the different sources of information, the assumptions on which the framework is founded are very similar. First, the different sources of information are independent. The same assumption has also been made by Irwin and Yeomans (1986; Yeomans & Irwin, 1985). Second, the contents of any one of, or all, the sources of information can be used to generate a response (Di Lollo & Dixon, 1988; Dixon & Di Lollo, 1991). In our framework, we elaborate this assumption by allowing that responses generated from a source of information need not be correct and that errors might occur because information from a source is distorted or inaccurate.

These assumptions not only have intuitive appeal, but, more importantly, allow for the generation of simple quantitative models. For example, the independence assumption entails that partial report performance is equal to the sum of the contributions of the different sources of information. Further assumptions regarding the nature of the sources of information allow specific models to be generated concerning the effects of particular independent variables. For example, Di Lollo and Dixon (1988) assumed that visible persistence decayed from the onset of a stimulus, whereas the visual analog decayed from the offset of a stimulus. As a consequence, they predicted that the ISI between the array and the probe should affect performance differently than the SOA between the array and the probe. The resulting quantitative model provided an accurate fit to their observed data. Dixon and Di Lollo (1991) used a similar approach to account for the effects of display luminance, stimulus meaningfulness, and probe duration in a partial report task.

Although Di Lollo and Dixon (1988; Dixon & Di Lollo, 1991) tested specific models, both models can be viewed as instances of the tripartite framework. As well, the models of Irwin and Yeomans (1986) and Mewhort et al. (1981) embody similar but less precise assumptions. Thus, the tripartite framework effectively captures and unifies the common elements of much of current theorizing concerning the mechanisms underlying partial report performance. Moreover, the framework can be used as a starting point for detailed formulations concerning the effects of independent variables. In the approach adopted here, we construct different versions of the tripartite framework in which the effect of cue duration is assumed to be isolated in different sources of information (verbal, visual features, or abstract identities). By comparing the adequacy of the quantitative fits, we can generate inferences about the nature of the effect and its role in information processing.

Accounts of the Cue-Duration Effect

In a bar-probe partial report task, as the duration of the visual probe increases, performance decreases (V. M. Townsend, 1973). This result seems counterintuitive, because there is no obvious reason why subjects should be unable to select information concerning the cued item as soon as the cue is visible; simply leaving the cue on the screen would seem to be irrelevant to performance. Furthermore, on the basis of the empirical evidence, there are several reasons why the effect cannot be explained by assuming that subjects wait until the offset of the cue to select items from the array (even granting that there was a plausible reason to do so). First, the effect of cue duration is not equivalent to inserting a comparable ISI; the effect of cue duration and the effect of ISI follow different time courses (Dixon & Di Lollo, 1991). Second, there is little effect of cue duration when the cue is an item and subjects decide whether the item is in an array (V. M. Townsend, 1973). Third, the simple expedient of making the bar longer decreases the size of the effect, and it is largely absent if the cue is spatially distanced from the item (Dixon et al., 1997). And fourth, the cue duration effect is much smaller when items are presented foveally rather than in the periphery (Di Lollo & Dixon, 1993). Thus, there is a complex pattern of effects and interactions that is not explained simply by assuming that long-duration cues impose some type of delay of processing.

In view of these kinds of results, a variety of accounts of the effect of cue duration have been proposed in the partial report literature. These various accounts make different predictions concerning which source of information is involved. V. M. Townsend (1973) suggested that the long-duration cues interfered with the process of locating visual identity codes. On this hypothesis, the target's identity code must be conjoined with the correct location code. V. M. Townsend assumed that the identity code remains relatively intact over time, whereas the location code becomes unreliable. Consequently, after a long-duration cue, subjects are less likely to conjoin the location code with the correct identity code. In our terms, this means that long-duration cues should decrease the utility of abstract identity information and, moreover, that the contribution of this store is specifically affected by cue duration.

Dixon and Di Lollo (1994) presented an account of the cue-duration effect that was based on the concept of temporal integration. They assumed that partial report performance improves whenever the array stimulus is temporally integrated with the cue, forming a single phenomenal whole. In order to account for the effect of cue duration, they proposed a quantitative model of how temporal integration is affected by the temporal configuration of the stimuli. In their approach, visual stimuli generate responses in the visual system that rise and fall relatively slowly. Consequently, visual responses may overlap substantially, even when the physical stimuli are disjoint in time. If the overlap is sufficiently extensive (as measured by a temporal correlation coefficient), the successive stimuli will be integrated into a single phenomenal whole. Similar ideas have been proposed by Groner, Bischof, and Di Lollo (1988) and Wolford (1993). The crucial element of this approach for the current investigation is that Dixon and Di Lollo (1994) argue that partial report performance is likely to be accurate if the array and the cue are temporally integrated and that this integration is more likely when the duration of either is brief. The net result is that a long-duration cue is less likely to be integrated with the array and does not enjoy the performance advantage of a brief cue. In our terms, the temporal integration approach implies that long-duration cues lead to a decrease in the ability to use visual feature information in the array.

Finally, the effect of cue duration has also been analyzed in terms of attentional processes. Dixon et al. (1997) reported eight experiments manipulating whether the endogenous or exogenous attentional system was used to select information from the array. Endogenous selection can be characterized as selection that is under voluntary control, whereas exogenous selection can be considered a reflexive response to external stimuli (see, e.g., Posner, 1980). Dixon et al. (1997) reported that an effect of cue duration was found only under conditions that favored exogenous selection. For example, an effect was found with a peripheral cue near the target location but was not found when the cue was near fixation and spatially removed from the target location; an effect of cue duration was found when the cue was uninformative, but not when the cue required some cognitive interpretation. Although these results strongly suggest the involvement of the exogenous selection system, it seems likely that attention is involved in selecting information both from visual identities and from visual features. Thus, the data and account offered by Dixon et al. are neutral with respect to the nature of the information involved in the effect: Either or both sources of information might be involved.

Plan of the Present Research

The aim of the present research was to isolate the source of information with which long-duration visual cues interfere. This was done by manipulating the temporal and visual parameters of the partial report task that are likely to affect either abstract identity codes or visual feature information. In order to evaluate the results, quantitative models were fit to the results. These models were based on the assumptions of the tripartite framework described above. What is important to note is that we use the tripartite framework as a basis of analysis; we believe the fundamental tenets of the framework are justified by a large body of empirical and theoretical work on partial report. Thus, we are not evaluating the framework per se but, instead, different models generated *within* the framework. As will be shown below, the best-fitting model incorporates the assumption that long-duration cues reduce the amount of visual feature information available to partial report but have no effect on abstract identity information. Consequently, on the basis of the model fits, we argue that long-duration cues interfere with visual feature information and do not interact with variables that affect only abstract identity information.

The central manipulation in this investigation involves the distance in the visual display between the target item and neighboring distracting information. A variety of research has shown that flanking information reduces the accuracy of reporting items from brief visual displays. J. T. Townsend, Taylor, and Brown (1971) found that identification accuracy improves when the flankers surrounding a target letter are replaced by blank spaces. That is to say, performance improves when the likelihood for local contour interactions decreases. Other research reports that when a target letter is surrounded by visually similar letters, identification accuracy is lower than if the target is flanked by letters that are visually dissimilar to the target (e.g., Estes, 1982; Krumhansl & Thomas, 1977). Still other researchers suggest that feature information drifts and may be recombined incorrectly with adjacent features (Irwin & Yeomans, 1986). Wolford (1975) also states that features of array items adjacent to the target interfere with the constituent features of the target, leading to an inaccurate report. On the basis of these results, the prediction in the present work becomes: As array density is increased, performance should decline. Following this research, we assume that abstract identities are affected by the proximity of other identity codes, whereas visual feature information is affected by the proximity of other visual features.

The partial report displays were constructed to provide independent manipulations of interference among abstract identity codes and interference among visual features. The array consisted of either 6 or 12 letters, together with a number of instances of the filler character #. The total size of the array, counting both letters and fillers, was either 18 or 24 items. The array items were arranged in circular pattern around fixation, so that the distance between adjacent items in the 24-item array was 25% less than that in an 18-item array. We assumed that this manipulation of distance would affect the accuracy of visual feature information. However, we also assumed that abstract identity information would be affected only by the proximity of nearby letters and would be relatively unaffected by adjacent fillers. Consequently, we manipulated whether there was 0, 1, or 2 filler items adjacent to the target item. Accuracy of abstract identity information should increase with the number of flanking fillers, whereas the accuracy of visual feature information should be less affected.

We also manipulated the ISI between the array and the cue. This manipulation provides another way of distinguishing visual feature information and abstract identities, because visual feature information is likely to decay quickly with increasing ISI, whereas abstract identities are assumed to be more stable. For example, Sperling (1960) reported that as ISI increased, performance declined, eventually reaching an asymptote comparable with whole report performance. We argued earlier that it is likely that this asymptotic level of performance reflects a stable but nonverbal source of information. Performance at short delays, however, is more likely to reflect the use of both labile feature information and abstract identity information. Consequently, if the effect of cue duration interferes primarily with labile feature information, the effect of cue duration should be more pronounced at short ISIs.

METHOD

Subjects

Seventeen undergraduates from the University of Alberta subject pool participated for class credit. All had normal or corrected-to-normal vision, based on self-report.

Stimuli

The stimuli were presented dark-on-light on a 33-cm monochrome video monitor. The space-average luminance of the stimuli was 29 cd/m^2, and the space-average luminance of the light background was 53 cd/m^2. Stimuli were uppercase letters of the English alphabet and filler items (all fillers were #s). Both letters and fillers were presented in 18-point Times font. Viewed at a distance of approximately 50 cm, items subtended approximately 0.69° vertically. Stimuli were presented on the perimeter of a notional circle of a radius of 2.95°. The cue was a radial line that started 1.91° from the center of the circle, was 0.59° in length, and terminated approximately 0.45° from the center of the target letter. Letters presented in the array were selected randomly each trial, under the constraint that no letter appeared**neutral** more than once in the array. The position of the target was also randomized on each trial.

Procedure

The subjects started each trial by pressing the mouse button. A central fixation dot remained on the screen for 450 msec. Following the offset of the fixation dot, the stimulus array was presented for 30 msec. After the array, a cue was presented for either 30 or 330 msec. The array and cue were separated by an ISI of 0 or 810 msec. After the stimulus sequence, five response alternatives

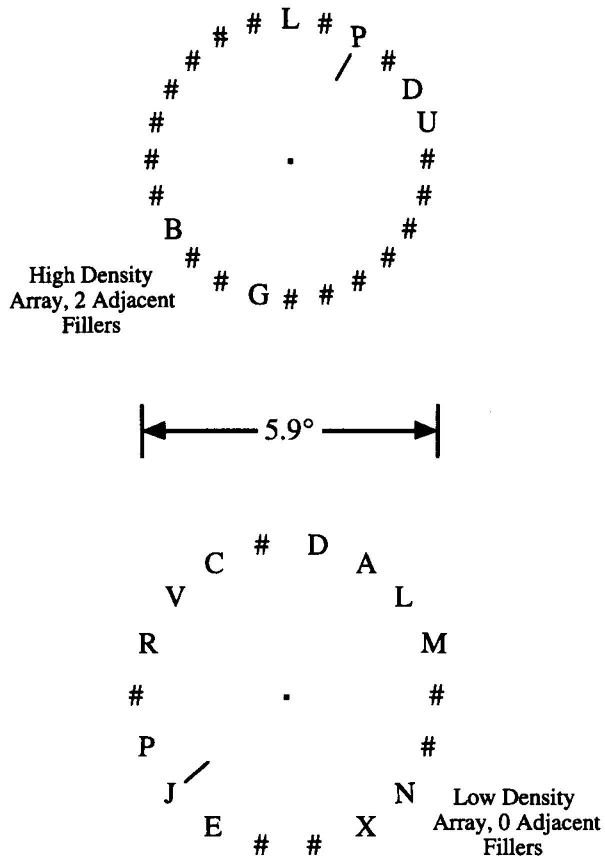

Figure 1. Sample stimulus configurations.

were presented on the screen, consisting of the target letter, the two letters that were presented nearest the target, and two randomly selected letters that did not appear in the array. The subjects indicated their response by clicking, with a computer mouse, on the letter that they thought was cued. The subjects were instructed to make their best guess if they were unsure of the correct answer. The subjects were able to pause as needed between trials, with longer breaks encouraged after each block of 48 trials.

Design

There were a total of 48 conditions in the experiment, consisting of the factorial combination of the following display characteristics: Number of flanking fillers (0, 1, or 2), cue duration (30 or 330 msec), number of letters in the array (6 or 12), number of items in the array (18 or 24), and the ISI between the array and the cue (0 or 810 msec). The number of flanking fillers was randomized within each block; the other factors were varied between blocks. An example of a stimulus configuration is shown in Figure 1.

Subjects completed 17 blocks of 48 trials, the first being a practice block. Each block consisted of 16 trials each with 0, 1, and 2 flanking fillers presented in a random order. The practice block used 18 item arrays with six letters, a 30-msec cue, and a 0-msec ISI. The succeeding 16 blocks consisted of the factorial combination of the cue duration, letters, items, and ISI factors. The presentation order of these blocks was randomized for each subject.

RESULTS AND DISCUSSION

Tables 1 and 2 present the mean accuracy and mean transposition errors, respectively, in each of the 48 conditions. The standard errors for each mean are computed from the error term in a repeated measures analysis of variance and are appropriate for pairwise comparisons (Loftus & Masson, 1994). Generally, all of the factors had substantial effects on performance. The only exception was number of letters; accuracy was only 2.2% better with 6 items than with 12.

In addition to the main effects, there were several interactions that must be noted. Cue duration and ISI interacted, so that, in the 0-msec ISI condition, the effect of cue duration was 18.9%, whereas, in the 810-msec ISI condition, the cue-duration effect was only 2.5%. Array density also interacted with ISI. The effect of array density was larger at short cue delays (9.5%) than at long cue delays (2.8%). Cue duration interacted with the number of flankers adjacent to the target. Although overall performance improved as the number of flankers increased, the effect of cue duration declined as the number of flankers increased. The cue-duration effect was 13.5% with two filler items, 9.7% with one filler, and 8.8% with zero fillers. The number of flankers also interacted with array density: With zero flankers, the effect of array density was 3.4%; with one flanker, it was 8.6%; and with two flankers, it was 6.5%. There was also a three-way interaction between array density, cue duration, and ISI. With no cue delay, the effect of cue duration was larger in the low-density condition (21.5%) than in the high-density condition (16.2%). On the other hand, with an 810-msec cue delay, the effect of cue duration was the same in the low- and high-density conditions (1.6% and 3.4%, respectively).

The trends in the transposition data are not as easy to interpret, because the number of transpositions is directly related to the number of overall errors (i.e., transpositions and intrusions). Thus, the theoretical importance of subtle trends in transpositions must be tempered by that relationship. With that in mind, the main pattern of interactions observed in the transposition data mirrors the patterns observed in the accuracy data. ISI interacted with cue duration and array density. When there was no cue delay, the effect of cue duration was 11.2%, as compared with 2.7% when there was an 810-msec delay. Similarly, when there was no cue delay, the effect of array density was 6.8%, as compared with 1.9% when there was an 810-msec delay. Cue duration also interacted with the number of flankers: The effect of cue duration was 4% with no flankers, 6.8% with one flanker, and 10.3% with two flankers. Finally, as the number of flankers increased, the effect of array density decreased. When there were no flankers, the effect of array density was 1.8%, as compared with an array density effect of 6.8% with one flanker and 4.4% with two flankers adjacent to the target.

A Quantitative Implementation of the Tripartite Framework

In order to disentangle and interpret the interactions observed in the results, a quantitative model based on the tripartite framework described in the introduction was fit to the results. In the model, we assume that three sources

Table 1
Predicted and Observed Proportion of Correct Responses as a Function of Flankers, Letters, Array Density, Cue Duration, and Interstimulus Interval (ISI)

ISI	Flankers	Letters	Density	Cue Duration	Responses: Predicted	Responses: Observed	Standard Error
0	0	6	18	30	.548	.581	.029
0	0	6	18	330	.342	.357	.029
0	0	6	24	30	.439	.434	.030
0	0	6	24	330	.305	.287	.019
0	0	12	18	30	.548	.507	.037
0	0	12	18	330	.342	.346	.025
0	0	12	24	30	.439	.467	.033
0	0	12	24	330	.305	.265	.025
0	1	6	18	30	.607	.629	.036
0	1	6	18	330	.382	.408	.039
0	1	6	24	30	.481	.445	.037
0	1	6	24	330	.334	.360	.039
0	1	12	18	30	.607	.625	.027
0	1	12	18	330	.382	.386	.030
0	1	12	24	30	.481	.482	.034
0	1	12	24	330	.334	.290	.034
0	2	6	18	30	.666	.658	.041
0	2	6	18	330	.422	.437	.040
0	2	6	24	30	.523	.552	.033
0	2	6	24	330	.364	.371	.036
0	2	12	18	30	.666	.636	.021
0	2	12	18	330	.422	.412	.038
0	2	12	24	30	.523	.526	.028
0	2	12	24	330	.364	.357	.013
810	0	6	18	30	.283	.291	.028
810	0	6	18	330	.283	.265	.037
810	0	6	24	30	.266	.291	.032
810	0	6	24	330	.266	.320	.034
810	0	12	18	30	.283	.257	.032
810	0	12	18	330	.283	.283	.030
810	0	12	24	30	.266	.276	.033
810	0	12	24	330	.266	.276	.033
810	1	6	18	30	.318	.327	.029
810	1	6	18	330	.318	.342	.020
810	1	6	24	30	.292	.294	.045
810	1	6	24	330	.292	.301	.018
810	1	12	18	30	.318	.312	.024
810	1	12	18	330	.318	.327	.033
810	1	12	24	30	.292	.287	.038
810	1	12	24	330	.292	.210	.030
810	2	6	18	30	.352	.386	.022
810	2	6	18	330	.352	.334	.025
810	2	6	24	30	.318	.397	.033
810	2	6	24	330	.318	.279	.023
810	2	12	18	30	.352	.390	.038
810	2	12	18	330	.352	.316	.038
810	2	12	24	30	.318	.305	.032
810	2	12	24	330	.318	.261	.032

of information contribute to performance: verbal information, visual identity information, and visual features. Thus, the probability correct can be written as

$$P(C) = V + (1 - V)I + (1 - V)(1 - I)F + (1 - V)(1 - I)(1 - F)k, \quad (1)$$

where V, I, and F correspond to the probability of information pertaining to the target item being available in verbal, identity, or feature information sources and k is the probability of guessing correctly ($k = .2$ in the present paradigm). This development is similar to the assumptions used by Di Lollo and Dixon (1988). However, we also assumed that even when information was available from an information source, errors might occur because that information was inaccurate. Consequently, Equation 1 was modified to include an accuracy factor for each source of information:

$$P(C) = Vw + (1 - V)Ij + (1 - V)(1 - I)Fg + (1 - V)(1 - I)(1 - F)k. \quad (2)$$

In order to use this model in understanding our results, we made specific assumptions about how these elements

Table 2
Predicted and Observed Proportion of Transposition Errors as a Function of Flankers, Letters, Array Density, Cue Duration, and Interstimulus Interval (ISI)

ISI	Flankers	Letters	Density	Cue Duration	Errors Predicted	Errors Observed	Standard Error
0	0	6	18	30	.331	.323	.032
0	0	6	18	330	.424	.434	.028
0	0	6	24	30	.386	.408	.026
0	0	6	24	330	.454	.500	.029
0	0	12	18	30	.331	.353	.033
0	0	12	18	330	.424	.364	.030
0	0	12	24	30	.386	.331	.026
0	0	12	24	330	.454	.445	.045
0	1	6	18	30	.279	.213	.028
0	1	6	18	330	.381	.393	.033
0	1	6	24	30	.348	.375	.033
0	1	6	24	330	.422	.382	.027
0	1	12	18	30	.279	.221	.024
0	1	12	18	330	.381	.386	.034
0	1	12	24	30	.348	.346	.028
0	1	12	24	330	.422	.452	.024
0	2	6	18	30	.228	.198	.035
0	2	6	18	330	.338	.338	.029
0	2	6	24	30	.310	.261	.029
0	2	6	24	330	.389	.408	.030
0	2	12	18	30	.228	.228	.026
0	2	12	18	330	.338	.342	.033
0	2	12	24	30	.310	.268	.022
0	2	12	24	330	.389	.434	.024
810	0	6	18	30	.462	.489	.023
810	0	6	18	330	.462	.566	.032
810	0	6	24	30	.482	.537	.035
810	0	6	24	330	.482	.467	.040
810	0	12	18	30	.462	.474	.029
810	0	12	18	330	.462	.467	.032
810	0	12	24	30	.482	.471	.032
810	0	12	24	330	.482	.460	.045
810	1	6	18	30	.423	.415	.024
810	1	6	18	330	.423	.419	.027
810	1	6	24	30	.452	.493	.041
810	1	6	24	330	.452	.467	.026
810	1	12	18	30	.423	.415	.025
810	1	12	18	330	.423	.437	.032
810	1	12	24	30	.452	.427	.034
810	1	12	24	330	.452	.507	.034
810	2	6	18	30	.383	.346	.025
810	2	6	18	330	.383	.416	.028
810	2	6	24	30	.423	.386	.033
810	2	6	24	330	.423	.434	.018
810	2	12	18	30	.383	.346	.030
810	2	12	18	330	.383	.452	.043
810	2	12	24	30	.423	.397	.033
810	2	12	24	330	.423	.430	.036

of the model would be affected by the experimental manipulations. In particular, we expected that the quantity and accuracy of verbal information, as well as the amount of identity information extracted from the display, would be unaffected by the factors manipulated here; in other words, V, w, and I were assumed to be constant. However, we anticipated that j, the accuracy of visual identity information, would be affected primarily by letter transpositions and that such transpositions would be a function of the distance between the target item and adjacent letters. Target–letter distance was primarily a function of whether the items adjacent to the target were letters or fillers but was also affected to a certain extent by the total number of items in the array. As a simple approximation, we assumed that accuracy is a linear function of d, the average distance to the nearest letter on either side:

$$j = \alpha + \beta d = \alpha + \beta\left(\frac{2+D}{2}\right)\left(\frac{2\pi r}{N}\right), \tag{3}$$

where D is the number of flanking fillers (0, 1, or 2), r is the radius of the circular array (2.95°), and N is the number of items in the array (18 or 24). Although we assumed a linear function, other functional relationships, such as an exponential or Gaussian, are likely to be more accurate (see, e.g., Ashby, Prinzmetal, Ivry, & Maddox, 1996). However, the limited range of interletter distance examined in the present study makes it difficult to distinguish empirically which of several plausible relationships would be most appropriate. For this reason, a simple linear function was used as an approximation to the true relationship.

A second assumption was that F, the amount of available feature information, would decline with increasing ISI. We use the notation F_0 to refer to the information available at 0 ISI and F_{810} to refer to the information available at the long, 810-msec ISI. Previous research has shown that most of the loss of information in partial report occurs within the first few hundred milliseconds (e.g., Dixon & Di Lollo, 1991); consequently, we assumed that $F_{810} = 0$.

Finally, we assumed that the accuracy of the feature information, g, would be affected by feature confusions between the target and adjacent items and that such confusions would be more likely to occur when items are close together than when they are farther apart. We approximated this accuracy function as a linear function of item separation, s. Thus,

$$g = \varepsilon + \gamma s = \varepsilon + \gamma 2 \pi r / N. \tag{4}$$

It seemed likely that the accuracy of feature information would also vary with the nature of the flanking items. In particular, we expected that feature confusions would be much more likely to affect the accuracy of target report when the adjacent items were visually confusable with the target than when they were dissimilar. Because the filler item, #, is similar to only some letters of the alphabet, feature confusions should be less likely to affect the accuracy of report when the adjacent item is a filler than when it is a letter. In order to generate an estimate of the relative confusability of the fillers and letters, we divided letters into three groups on the basis of visual similarity. These groups consisted of letters consisting of only horizontal and vertical line segments (E, F, H, I, L, T), letters containing diagonal elements (A, K, M, N, V, W, X, Y, Z), and letters containing curved segments (B, C, D, G, J, O, P, Q, R, S, U). We assumed that accuracy of reporting the correct item would be related to the likelihood that the target and the flanking stimulus come from different groups. When the flanking stimulus is another letter, the probability of not being visually confusable (i.e., coming from different groups) is

$$c_L = 1 - \left[\left(\frac{6}{26}\right)^2 + \left(\frac{9}{26}\right)^2 + \left(\frac{11}{26}\right)^2 \right] = .65.$$

However, when the flanking stimulus is a filler character, the target is likely to be confusable only when it comes from the group of horizontal/vertical letters. Consequently, the probability of the target not being confusable with an adjacent filler is just the probability that the target is not a horizontal/vertical letter:

$$c_F = 1 - \left(\frac{6}{26}\right) = .77.$$

This confusability factor was incorporated into the accuracy of feature information by assuming that the accuracy was $c_L g_N$ when the adjacent items were letters (where N is either 18 or 24), $c_F g_N$ when the adjacent items were fillers, and halfway in between when the target was flanked by a filler on one side and a letter on the other. We refer to this visual confusability factor as C_D, defined as

$$C_D = \begin{Bmatrix} c_F, \text{target flanked by filler characters} \\ c_L, \text{target flanked by letters} \\ \dfrac{c_L + c_F}{2}, \text{target flanked by one filler and one letter} \end{Bmatrix}.$$

There are four identifiable parameters in this model. The first reflects the overall level of performance and is determined by the verbal information source together with the constant portion of the identity information, as follows:

$$V' = Vw + (1 - V)I\alpha + (1 - V)(1 - I)k. \tag{5}$$

The second parameter reflects the increase in accuracy of identity information with increasing distance:

$$I' = (1 - V)I\beta. \tag{6}$$

The third reflects the amount of feature information available at 0 ISI:

$$F' = (1 - V)(1 - I)F_0\varepsilon - (1 - V)(1 - I)F_0 k. \tag{7}$$

Finally, the fourth parameter is the increase in feature accuracy with spatial separation between adjacent items:

$$N' = (1 - V)(1 - I)F_0\gamma. \tag{8}$$

Putting these equations together, the total accuracy at 810-msec ISI is

$$P(C) = V' + I'd. \tag{9}$$

At 0 ISI, there two additional terms representing the contribution of feature information:

$$P(C) = V' + I'd + F'C_D + N'C_D s. \tag{10}$$

This framework can also be used to predict the rate of transposition errors. In particular, transposition errors are primarily related to inaccurate identity information, as described above; following from Equation 2, the probability of a transposition error arising from inaccurate identity information would be $(1 - V)\,I\,(1 - j)$. However, transpositions can also occur by chance whenever subjects guess. In the present paradigm, subjects select their response from among five alternatives, consisting of the target, the two flanking items, and two items not in the array. Consequently, the probability of an error being a transposition when subjects are guessing is .5. Guessing would occur in two ways. First, subjects would have to guess when they have no information pertaining to the target; from Equation 2, the probability of having no information is the term $(1-V)(1-I)(1-F)$, and consequently, the probability of a transposition being generated in this case would be $(1-V)(1-I)(1-F)(1-k)/2$. Guessing can also occur when subjects have inaccurate feature or verbal information, because the item suggested by their information would not be among the alternatives. From Equation 2, the probability of having inaccurate feature or verbal information is $V(1-w)+(1-V)(1-I)F(1-g)$, and the probability of a transposition error resulting from these kinds of erroneous information would be half of that $[V(1-w)/2+(1-V)(1-I)F(1-g)/2]$. Thus, the total probability of a transposition error would be the sum of these terms:

$$P(T)=(1-V)I(1-j)+\frac{(1-V)(1-I)(1-F)(1-k)}{2}+\frac{V(1-w)}{2}+\frac{(1-V)(1-I)F(1-g)}{2}.$$

Many of the elements in this equation also appear in Equation 2 for the probability correct, and by rearranging the terms, this equation can be rewritten as

$$P(T)=\frac{1}{2}\left[1-P(C)\right]+\frac{(1-V)I(1-j)}{2}.$$

Using Equation 3 to expand j, this becomes

$$P(T)=\frac{1}{2}\left[1-P(C)\right]+\frac{(1-V)I(1-\alpha-\beta d)}{2}.$$

Because V and I were assumed to be constant across the conditions used here, the probability of a transposition can be written as

$$P(T)=T'-\frac{P(C)}{2}-\frac{(1-V)I\beta d}{2},$$

where T' is a constant term defined as

$$T=\frac{1}{2}+\frac{(1-V)I}{2}-\frac{(1-V)I\alpha}{2}. \tag{11}$$

Finally, from Equation 3, the probability of a transposition is

$$P(T)=T'-\frac{P(C)}{2}-\frac{I'd}{2}.$$

In this development, T' determines the overall level of transposition errors and is the only parameter that needs to be estimated beyond those identified in Equations 5–10.

We refer to the assumptions embodied in this quantitative development of the tripartite framework as the tripartite model of partial report, based as it is on the view that performance depends on the conjunction of verbal information, abstract identity information, and feature information. Below, we compare several ways of incorporating effects of cue duration in this general framework.

Model 1: Effects on Visual Feature Information

One plausible working hypothesis is that the effect of cue duration interferes with labile visual feature information. There are several possible mechanisms that could be at work here. For example, it could be the case that a long-duration cue makes it difficult to align the array and the cue in a temporally integrated visual percept (see, e.g., Dixon & Di Lollo, 1994). Another possibility is that the cue acts as a mask and that a long-duration cue is more effective in that role. Still another possibility is that, when using a long-duration cue, selection occurs over a longer period of time and that, during this time, feature information becomes unreliable (Dixon et al., 1997). Although the manipulations used in the present study do not permit us to distinguish these possibilities, using the present approach, we can evaluate the assumption common to these different accounts—namely, that the cue-duration effect reduces the utility of feature level information.

To test this hypothesis, Model 1 incorporates the effect of cue duration into the visual feature source of information. In terms of model parameters, making this assumption requires that the last two terms in Equation 10 be multiplied by an additional factor, P', in the long-duration cue conditions. That is, accuracy for long cue durations should be

$$P(C)=V'+I'd+P'F'C_D+P'N'C_D s. \tag{12}$$

The model generated by Equations 9, 10, and 12 was fit to the obtained data shown in Table 1, using a gradient descent procedure that maximized the likelihood of the data. Likelihoods were calculated on the assumption that each data point consisted of an independent sample from a binomial distribution. In other words,

$$L(X_i)=\binom{n}{nX_i}(nX_i)^{p_i}(n-nX_i)^{1-p_i}, \tag{13}$$

where X_i is the observed accuracy rate and p_i is the predicted accuracy rate for each condition i; since the data in each condition are independent, the total likelihood is the product of the likelihoods for each condition $[L=\Pi L(X_i)]$. The actual fitting was done with the logarithm of this likelihood; this allowed us to estimate parameters by simply maximizing the sum of the log likelihood for each of the conditions—that is, $\log L=\Sigma \log L(X_i)$.

The parameter estimates for Model 1 are shown in Table 3, and the overall fit of the model is shown in Figure 2. (In this and subsequent plots, the data are collapsed over number of letters in the array, since this factor had little effect on performance.) The root-mean squared deviation from the model predictions was .029 with an R^2 value of .932. A chi-square goodness-of-fit test revealed that the observed data did not significantly differ from the predictions made by Model 1 $[\chi^2(43)=33.27, p>.85]$. The accuracy of the fit can be seen in Figure 2, where virtually all the observed data points are within a standard error of the predicted values. Indeed, the greatest difference between observed and predicted for the 24 points was .047. In order to illustrate the account the model pro-

Table 3
Estimated Model Parameters

Parameter	Model 1	Model 2	Model 3
V'	.214	.218	.273
I'	.067	.103	.064
F'	−.155	−.147	−.155
N'	.547	.385	.394
P'	.224	.294	.633

vides of the experimental results, we provide leverage plots below for the predicted effects related to feature and identity information.

Care must be taken in interpreting the values of the parameters in Table 3 in terms of the processes assumed in the model. For example, the parameter F' is determined in part by the intercept of the linear function relating accuracy of feature information to item separation (i.e., ε in Equation 4). It is plausible to assume that this intercept value is close to zero, since the discriminability of visual features should become quite low as the item separation becomes very small. However, because of the manner in which the model is parameterized, F' reflects not just the value of this zero intercept, but rather the magnitude of ε, relative to the accuracy of guessing, k. Thus, the negative value of F' indicates that the accuracy of responding based on feature information (when the item separation is 0) is less than the accuracy that would be obtained simply by guessing; in other words, ε must be less than k in Equation 5.

Figure 3 shows the leverage for the identity source of information. The data points indicate the observed values, less the predicted accuracy due to feature information. The curve shows the predicted linear function $V' + I'd$ (i.e., the predicted values, less the accuracy attributed to feature information). A leverage plot of this sort allows one to assess how successful a particular model component is in accounting for effects in the data. For example, the generally accurate fit in this case demonstrates that there is little systematic effect of cue duration that cannot be attributed to feature information. Similarly, the fit also shows that the effect of interletter distance isolated by the model does not interact with ISI; although the long-ISI data are somewhat noisier, there is little apparent systematicity to the deviations from the predicted line.

Figure 4 shows the leverage for the feature source of information. Analogous to Figure 3, this figure shows the observed data points, less the predicted accuracy due to identity information (i.e., $I'd$) and scaled for equivalent values of visual confusability (i.e., C_D is removed from the predicted and observed values). The curves on the left show the predicted linear functions of interitem separation [$P(C) = V' + F' + N'$s and $P(C) = V' + P'F' + P'N'$s]. The curve on the right shows the predicted constant level of performance at long ISIs (V'). The accurate fit shows that there is little effect of cue duration at long ISI, and that at short ISIs, the effect of cue duration interacts with separation. In particular, the interaction between cue duration and separation has the overadditive form characteristic of a multiplicative effect like that predicted in Equation 11. The qualitative form of the interaction is predictable from the intuitive notion that effects are likely to be smaller when the overall level of performance is low; for example, interitem separation has less of an effect on long cue duration trials than on short cue duration trials. In effect, the model provides a precise formulation of this intuition in the assumption of a multiplicative relationship between cue duration and feature information.

Although the multiplicative interaction between cue duration and interitem separation supports Model 1, it might be argued that the multiplicative interaction observed in these results is a function of the response scale and that such an interaction would not be observed if proportion correct were rescaled in some fashion (see, e.g., Loftus, 1985). We cannot rule out this possibility. However, it is our view that such rescaling requires a theoretically guided appraisal of how proportion correct is related to the underlying processes and constructs; such an appraisal is necessary, for example, to select the appropriate scale transformation and to interpret the rescaled results. With this in mind, the tripartite framework already entails specific assumptions concerning how proportion correct is related to underlying process and representations; consequently, further rescaling is not necessary. Indeed, the decomposition of the patterns of accuracy, as shown in Figures 3 and 4, is a type of (theoretically motivated) rescaling in terms of underlying theoretical constructs. Although it is certainly possible to select a different transformation (and to have different patterns of results by virtue

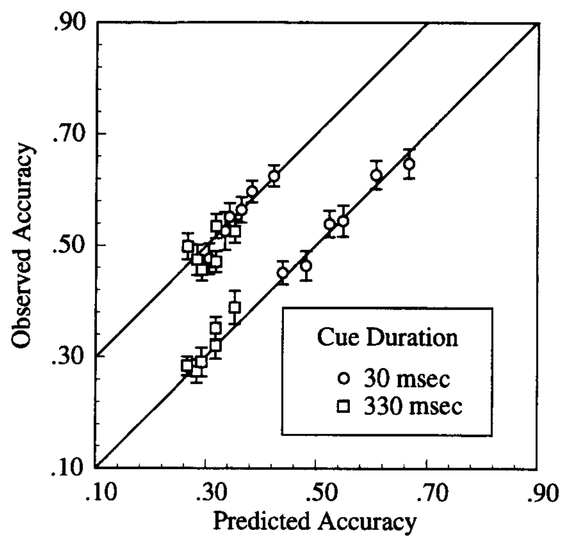

Figure 2. Predicted versus observed accuracy for Model 1. Data points in the 810-msec interstimulus interval conditions are offset .2 for clarity. Error bars in this and subsequent figures represent standard errors, on the procedure suggested by Loftus and Masson (1994) for repeated measures designs.

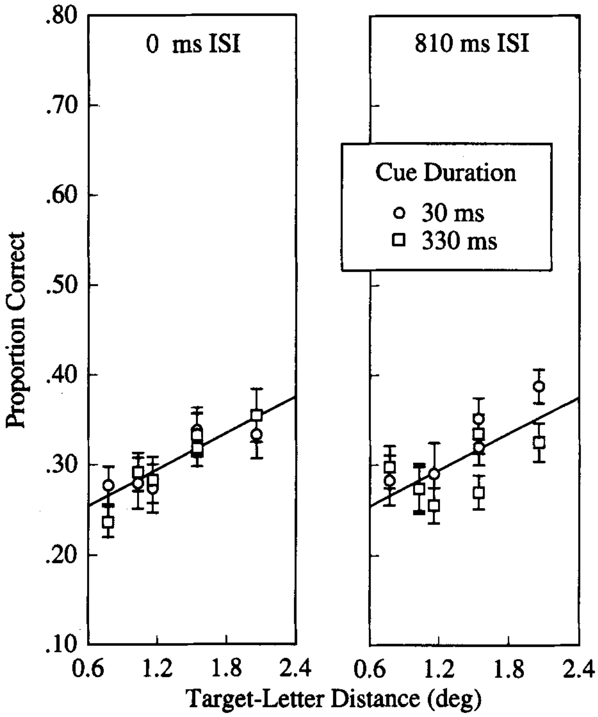

Figure 3. Leverage plot for the identity source of information as a function of interstimulus interval, cue duration, and the visual angle between the target and the nearest letter. Data points indicate the observed values, less the predicted accuracy owing to feature information. Solid lines represent the values predicted by Model 1, less the predicted accuracy owing to feature information.

of that transformation), the choice of transformation is, in effect, a choice of different theoretical approach; we have argued that the framework adopted here is the most defensible one on the basis of the extant literature on partial report.

The model also provides an accurate account of the rate of transposition errors. Figure 5 shows the overall accuracy of the fit. The root-mean squared deviation from the model predictions was .036. As with the accuracy data, a goodness-of-fit test revealed that the observed transposition data did not differ significantly from the predicted transpositions [$\chi^2(47) = 42.98, p > .47$]. The accurate fit is almost entirely due to the parameters estimated for accuracy, as shown in Equation 11; only the overall rate of transposition errors was estimated from these data. Thus, the substantial correlation apparent between the predicted and observed values ($R^2 = .840$) was predicted with no free parameters.

Model 2: Effects on Abstract Identity Information

Within the tripartite framework, it is also possible to evaluate alternative hypotheses concerning the effect of cue duration. In particular, we fit the model to the data on the assumption that cue duration decreases the accuracy of location information associated with abstract identity codes. Such a model might correspond, for example, to the hypothesis advanced by V. M. Townsend (1973). In terms of model parameters, this hypothesis suggests that, with long-duration cues, accuracy should not improve less as interletter distance is increased; in other words, I' in Equations 9 and 10 should be smaller. To capture this hypothesis, the second term in Equations 9 and 10 was multiplied by P' (rather than the third and fourth terms as in Model 1). That is, Equation 9 became

$$P(C) = V' + P'I'd,$$

and Equation 10 became

$$P(C) = V' + P'I'd + F'C_D + N'C_Ds.$$

This model was fit, using the same procedure as before.

The overall fit of this model was substantially worse than that of Model 1, with a root-mean squared deviation of .047 and an R^2 value of .808. This conclusion is supported by a goodness-of-fit test that revealed that the observed data differed significantly from the predictions made by Model 2 [$\chi^2(43) = 88.61, p < .001$]. The source of the poor fit is clearly shown in the leverage plot for the feature information source (Figure 6). As can be seen, the model fails to account for the relative lack of an effect of cue duration at long ISIs and underestimates the effect of cue duration at 0-msec ISI.

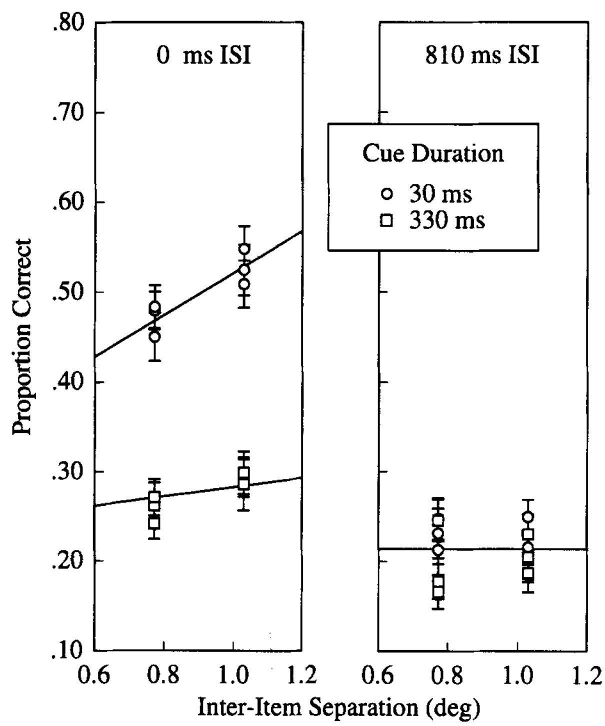

Figure 4. Leverage plot for the feature source of information as a function of interstimulus interval, cue duration, and the visual angle between the target and the nearest item. Data points indicate the observed values, less the predicted accuracy owing to identity information. Solid lines represent the values predicted by Model 1, less the predicted accuracy owing to identity information.

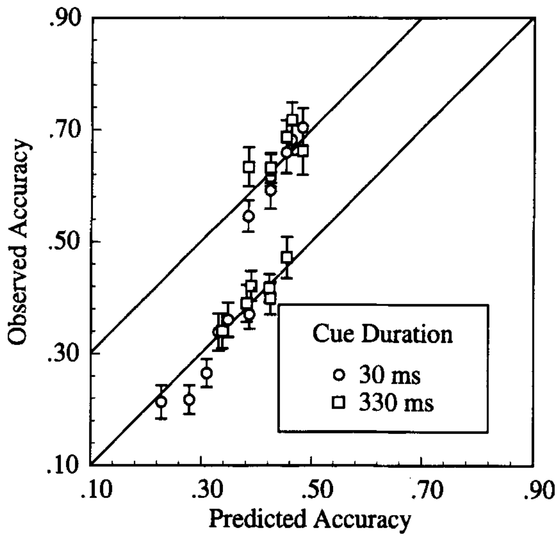

Figure 5. Predicted versus observed transpositions for Model 1. Data points in the 810-msec interstimulus interval conditions are offset .2 for clarity.

Model 3: Effects on Verbal Information

Although it has not been discussed in the literature, it is logically possible that the effect of cue duration is specific to the use of verbal information. Perhaps long-duration cues interfere with a maintenance mechanism, such as rehearsal. This generates the prediction that the V' parameter in Equations 9 and 10 should be smaller with long-duration cues. The new versions of the equations for this model would be

$$P(C) = P'\,V' + I'd$$

and

$$P(C) = P'\,V' + I'\,d + F'\,C_D + N'\,C_D\,s.$$

The results of fitting this model to the obtained data are similar to those obtained for Model 2, with a root-mean squared deviation of .050 and an R^2 value of .802. The results of a goodness-of-fit test were also similar to those for Model 2: The observed data differed significantly from the predictions made by Model 3 [$\chi^2(43) = 92.49$, $p < .001$].

Figure 7 shows the leverage plot for the feature information source and illustrates the nature of the problem in this model. As in Model 2, the effect of cue duration is underpredicted at an ISI of 0 msec and overpredicted at 810 msec. In contrast, Model 1 provides an accurate account of this pattern, because it is based on the assumption that cue duration affects feature information and feature information is largely unavailable at long ISIs.

GENERAL DISCUSSION

The aim of the present research was to isolate the locus of the effect of cue duration. It was argued that the effect of cue duration could be explained by a model that isolates cue duration with other factors that affect visual feature information. This hypothesis was supported by the fit of a quantitative model in which three different sources of information used in the partial report task are disentangled. This model allows performance to be predicted, using five parameters. The resulting fit provided an accurate description of the observed data, accounting for over 93% of the variance in observed scores.

The model provides an accurate account of a variety of trends in the results. First, it correctly predicts that effects of cue duration interact with ISI and that there is essentially no effect of cue duration with an ISI of 810 msec. Second, the model predicts the form of the interaction between cue duration and interitem spacing: Greater cue-duration effects are observed with larger spacing, and the increase is multiplicative, as predicted by the model. Both of these results are clear from Figure 4. Third, the model correctly predicts that the difference between letters and fillers does not interact with the cue-duration effect. In other words, although inter*letter* distance has an effect independent of inter*item* distance, this effect is the same at both levels of cue duration, as is shown in Figure 3. Fourth, the model also can accurately predict transposition errors. Taken together, these effects suggest that extended cue duration interferes with information that is short lived

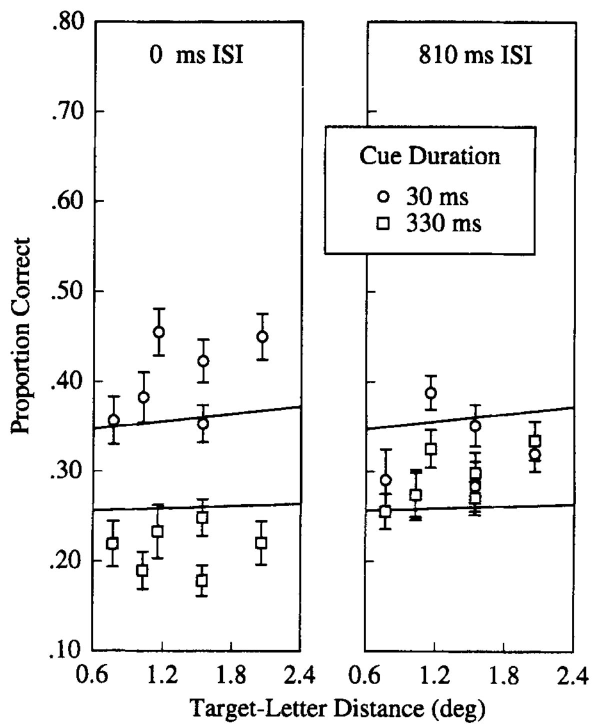

Figure 6. Leverage plot for the feature source of information as a function of interstimulus interval, cue duration, and the visual angle between the target and the nearest letter. Data points indicate the observed values, less the predicted accuracy owing to identity information. Solid lines represent the values predicted by Model 2, less the predicted accuracy owing to identity information.

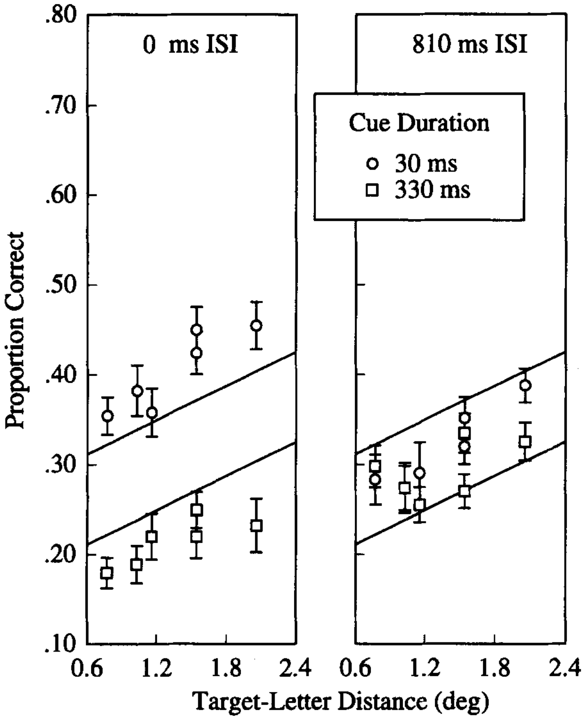

Figure 7. Leverage plot for the feature source of information as a function of interstimulus interval, cue duration, and the visual angle between the target and the nearest letter. Data points indicate the observed values, less the predicted accuracy owing to identity information. Solid lines represent the values predicted by Model 3, less the predicted accuracy owing to identity information.

(because the cue duration has little effect at long ISIs) and that is specific to visual form rather than to abstract identity (because there is little interaction between items and fillers).

Model 1 captures these trends in a quantitative form, and the accurate fit of the model provides evidence for these effects. A model that does not incorporate these trends would not fit as well, and a model that predicted other trends that are not present in the data would fit no better, while having more parameters. Models 2 and 3 show two alternatives within the tripartite framework that fail to capture the trends in the data in a suitable fashion. The result is demonstrably less accurate fits, as is shown in Figures 6 and 7. The leverage plots for Model 1 illustrate that all of the parameters are essential and that there appears to be little systematic deviation that could be captured by including additional parameters. Thus, within the constraints of the tripartite framework and related formulations, Model 1 would seem to provide the most accurate and parsimonious account of the cue-duration effect in the present experiment. Of course, different patterns of obtained results could easily have supported Model 2 or 3 rather than Model 1. For example, if the effect of cue duration had been stronger at the long-duration ISIs, or if the effect had been modulated by the difference between items and fillers, Model 2 might have provided the more accurate account. Thus, the comparison of fits from several models of comparable complexity provides insight into precisely which aspects of the modeling enterprise are required for accurate predictions.

Even though the results of the model fits support the notion that cue duration interferes with visual feature information only, Models 2 and 3 do not comprise an exhaustive list of the alternatives to Model 1. Other possibilities could include models that incorporate effects of cue duration into multiple sources of information. However, such models would require more complex theoretical analyses and quantitative implementation, without being able to account for much more of the variance in observed scores. Although data from other experiments might require such more complex formulations, the present analysis (that the interference caused by cue duration is localized solely to visual feature information) is adequate to account for the present pattern of results.

Although it has been shown that visual feature information is reduced by long cue duration, the evidence provided here does not provide much constraint on *how* the information is reduced. However, the current work is consistent with a mechanism recently proposed by Dixon et al. (1997). Their model is based on two assumptions: Selection of information from the array is tied to the spatiotemporal characteristics of the cue, and information from the array becomes unreliable as it decays. Dixon et al. suggest that visual cues indicate not only a region of the visual field from which information is be selected, but also a period of time over which information is to be selected. Thus, when a long-duration cue is presented, selection from the information about the array occurs over a longer period of time. However, because array information becomes less reliable over time, selecting information about the array for a longer period of time leads to less accurate information about the target item, and performance suffers. Dixon et al. suggested that the decrease in accuracy was due to the loss of location information about array items, but the evidence they present is equally consistent with the evidence presented here that the cue-duration effect is related to the loss of visual feature information.

On the basis of these converging lines of evidence, then, we suggest the following description of the effect of cue duration. After a brief display, subjects have available at least three kinds of information: visual features, abstract identities, and verbal codes. Verbal information and abstract identity information decay relatively slowly and so can be used strategically by the subject to choose the best response. However, in order to make use of feature information, attention must be directed quickly to the target position of the target. We hypothesize that the relatively poor performance with long-duration cues occurs because subjects are led to attend to the decaying visual feature information long after it is useful to do so. Consequently, the visual feature information that is extracted from the array becomes unreliable if a long-duration cue is used to direct attention, and performance suffers. The present results indicate that this effect is not observed at long ISIs, because performance is based primarily on verbal and abstract identity codes rather than on visual feature information.

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