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Multidimensional Models and Iconic Decay: Reply to Di Lollo and Dixon

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We discuss two issues raised by Di Lollo and Dixon. First, we formalize the notion of "informational dimensionality" and demonstrate that Loftus's extraction-rate model is equivalent to Di Lollo and Dixon's "dual-decay model" with respect to dimensionality. Second, we describe how the extraction-rate model can be modified to apply it to 2 data sets reported by Di Lollo and Dixon. The major modifications involve (1) the assumption of capacity limitations in short-term memory and (2) the assumption of differential information-extraction rates prior to and after probe presentation in a partial-report paradigm. We demonstrate that although the model can account qualitatively for Di Lollo and Dixon's data, it cannot account for them quantitatively.

Loftus and his colleagues have proposed a model of information extraction from visual stimuli and of the relationship between extracted information and subsequent memory performance. Briefly, this model, to which we henceforth refer as the *extraction-rate model*, makes the following assumptions. First, a visually presented stimulus engenders a function, $a(t)$, that characterizes *available information* that is potentially extractable by the observer at time t following stimulus onset. Second, information is extracted according to some instantaneous rate function, $r(t)$, that is the product of two entities: $a(t)$ and some function, h, of already-extracted information. Third, extracted information is unidimensional. Fourth, subsequent memory performance is monotonically related to extracted information. The model has successfully accounted for data from a variety of experimental paradigms involving both visual memory and visible persistence. Reviews are provided by Loftus and Hogden (1988), Loftus, Hanna, and Lester (1988), Loftus and Hanna (1989), and Loftus, Duncan, and Gehrig (1992).

Di Lollo and Dixon (1992; see also Di Lollo, 1985) have criticized the extraction-rate model principally because of its unidimensionality assumption. They point out that most visual-perception–memory models have incorporated some form of multidimensionality (e.g., Irwin and Yeomans 1986, and Mandler and Parker, 1976, posited separate decay of item and location information). Furthermore, Di Lollo and Dixon (1988, 1992) offer partial-report data that, they claim, disconfirm a unidimensional model such as the extraction-rate model. These data issue from a paradigm in which the stimulus, a circular array of letters, is displayed for varying durations and is followed at varying interstimulus intervals (ISIs) by a probe indicating a single to-be-reported letter. Di Lollo and Dixon found the usual inverse-ISI effect: Performance decreased with increasing ISI. They also found an inverse-*duration* effect: Performance decreased with increasing stimulus duration. Although common in temporal-integration tasks (cf. Di Lollo, 1980), an inverse-duration effect had never been previously reported in partial report, wherein performance is typically independent of stimulus duration (cf. Sperling, 1960).

Both the inverse-ISI and the inverse-duration effect are accounted for by a model described by Di Lollo and Dixon (1988), who presently (DiLollo and Dixon, 1992) credit this success to their model's multidimensional nature: It posits two iconic-decay functions, one initiated by stimulus onset and the other initiated by stimulus offset.

The remainder of this article is divided into two sections. First, we discuss and formalize the notion of multidimensionality and delineate the relation between the extraction-rate model on the one hand and Di Lollo and Dixon's (1988) model on the other. Second, we demonstrate that the extraction-rate model can account qualitatively but not quantitatively for Di Lollo and Dixon's data.

Multidimensionality

We agree with Di Lollo and Dixon (and with many others) that encoding a visual stimulus entails acquisition of various different information types. Accordingly, one can formulate a generic, relatively noncontroversial model in which, given J such types, or *dimensions*, the eventual stored memory representation can be characterized by the memory vector

$$\mathbf{M} = (I_1, I_2, \ldots, I_J), \tag{1}$$

where I_j is the value achieved on the jth informational dimension under some set of experimental circumstances (e.g., a partial-report stimulus displayed for d ms followed by a probe at an a-ms ISI).

Performance on any later memory test is based on the memory vector $\mathbf{M}$. The exact nature of the memory-vector/

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performance correspondence depends on the precision with which the informational dimensions, $I_1, I_2, \ldots, I_J$, are defined, along with the precision with which they are related to the dependent variable(s) measured in the memory test. In the most complete theory–data configuration, one might design an experiment in which an arbitrary number of dependent variables (e.g., two dependent variables, one measuring item knowledge and another measuring location knowledge) are assumed to assess individual I_js (e.g., one I corresponding to item information and another corresponding to location information). More commonly, however, investigators measure (or at least report) only a single performance measure, which we term P. To relate P to **M**, one can define a unidimensional construct called *extracted information* to be some function of the J, I values; that is,

$$I = f(I_1, I_2, \ldots, I_J), \tag{2}$$

where f is monotonic (usually strictly monotonic) in all its arguments. One can then assume performance to be a monotonic function of information; that is,

$$P = m(I). \tag{3}$$

One remark is in order here. In the present description, information, I, is unnecessary in the sense that one could relate P directly to **M**. Having a theoretical construct corresponding to "information," however, provides the most general, flexible, and intuitive characterization of the memory system (cf. Loftus & Hogden, 1988).

Two Versions of This Generic Model

We emphasize that the model we have just described is quite *general* in that the informational dimensions, $I_1, I_2, \ldots, I_J$, can be given any interpretation whatsoever. In our implicit example, they corresponded to item and location information, as described by Irwin and Yeomans (1986), for example. We now show that both Loftus's extraction-rate model and Di Lollo and Dixon's model are versions of this general model; that is, they both satisfy Equations 1–3. Accordingly, the models are formally equivalent with respect to the dimensionality issue.

The extraction-rate model. The extraction-rate model is a version of this generic model (i.e., a model satisfying Equations 1–3). As Di Lollo and Dixon (1992) point out by quoting Loftus et al. (1992), the model leaves the value of J along with the exact informational dimensions unspecified, noting only that there is some kind of many-to-one mapping of the J informational dimensions onto the unidimensional information that is explicitly used in the model. Loftus et al. summarize by noting that "By this definition *information* is unidimensional, whereas the *memory representation* is multidimensional" (p. 533).

Di Lollo and Dixon criticize this theoretical strategy on the grounds that it assumes an inappropriate quantitative combination of what are presumably qualitatively different information types. We feel that this criticism is unjustified. Any model (including Di Lollo and Dixon's) must eventually combine different information types to predict the results of any experiment in which only a single, global, dependent variable is measured (as, e.g., in Loftus et al. and in the data reported by Di Lollo & Dixon, 1988, 1992). Equations 2 and 3 provide what we believe to be the most general means of representing such combination.

The Di Lollo and Dixon model. Di Lollo and Dixon (1988) offered a version of the generic model (satisfying Equations 1–3) in which $J = 3$: I_1 is information based on *visible persistence* (of the original stimulus), I_2 is information based on a *visual analog* (representation of the original stimulus), and I_3 is information based on *guessing and other memory stores.* In the Di Lollo and Dixon model, I_1, I_2, and I_3 are expressed as probabilities, the function f is the combination rule for the union of independent probabilities, and m is the identity function.[1]

Information Combination and Informational Metamers

We now offer some additional remarks about the notion of combining information types when the model's job is to predict the value of a single performance measure. We have claimed that the only reasonable way a model can do this is to posit some function that maps **M**, the multidimensional memory structure, onto I, a unidimensional information scale that can then be mapped onto a unidimensional performance scale. Di Lollo and Dixon remark that if the different informational types are qualitatively different from one another, then combining them quantitatively (as in Equation 2) makes little sense.

We agree that quantitative combination of qualitatively different things is intrinsically awkward. One can, however, avoid this theoretical pitfall. Suppose that there are two (or more) experimental conditions (e.g., two different physical stimuli) that produce the same values of $I_1, \ldots, I_J$. Following color-vision terminology, let us call these *metameric conditions* and the corresponding stimuli *informational metamers.*

Two or more metameric stimuli are, of course, metameric independent of whatever rule maps the dimensions onto the unidimensional "information." A theory designed to specify conditions under which metamers are produced, or an experiment designed to ask whether such metamers even exist, thus finesses the problems entailed in trying to determine the appropriate rules for quantitative combination of qualitatively different information dimensions. This strategy has long been used in the vision literature to investigate color vision (e.g., Stiles, 1978; Von Helmholtz, 1896) and spatial vision (e.g., Nielson & Wandell, 1986) but has been used only sporadically in the perception–cognition literature (e.g., Bamber, 1979;

[1] It is important to note that $I_1, \ldots, I_3$, constitute information that has been accumulated by perceptual processes and that is present in memory when a response is made—which, of course, is after the stimulus presentation has long been completed. Although Di Lollo and Dixon do not explicitly say so, this information must be based on some integral over time of information that is available during stimulus presentation. Although, for example, available visual analog information declines over time since stimulus offset, the amount of such information that is transferred to more permanent storage *increases* over this same time.

Loftus & Bamber, 1990; Loftus et al., 1992; Palmer, 1988). In Loftus et al. in particular, the theoretical and empirical strategy was to determine rules by which stimulus duration and stimulus-mask ISI combine to produce metameric memory representations.

The Extraction-Rate Model's Application to Di Lollo and Dixon's Data

The extraction-rate model has been applied, apparently successfully, to the Di Lollo and Dixon (1988) data (see Loftus & Hanna, 1989, pp. 388–394). However, this application was based on somewhat shaky logic. We now present an extension of the model designed to account for partial report in general and for the Di Lollo and Dixon (1988, 1992) data in particular.[2] We show that the model succeeds qualitatively but fails quantitatively in this enterprise. Because we have added assumptions to give the model every chance to account for the data, we regard its quantitative failure as a telling boundary condition.

In what follows, we first reapply the model to Di Lollo and Dixon's (1988) partial-report data. These data issue from a Duration × ISI factorial design that is the same as their present (Di Lollo & Dixon, 1992) design but which incorporated a greater number of duration–ISI combinations (8 durations ranging from 10 to 500 ms × 5 ISIs ranging from 0 to 200 ms). We then apply the model to Di Lollo and Dixon's (1992) present data.

Model Modifications

Three modifications are required to apply the extraction-rate model to partial report.

1. In Loftus et al. the relevant stimulus consisted of only four digits, which does not exceed short-term memory capacity. Accordingly, it was assumed that with sufficient stimulus duration, all digits could be transferred to short-term store and recalled. Di Lollo and Dixon, however, used a 15-letter array, which far exceeds short-term memory capacity. Accordingly, we assume that amount of preprobe extracted information (from all stimulus locations, including the target location) increases over time toward some less-than-1.0 asymptote, the value of which is another model parameter.

2. Any model of the partial-report paradigm must assume some processing change following probe presentation that reflects attentional narrowing to the target letter from the array as a whole. The exact nature of this change is suggested by Reinitz (1990), who found that increasing attention to a target location increases the information-extraction rate from that location. Accordingly, we assume a postprobe change in $r(t)$, the magnitude of which is a model parameter.

3. Di Lollo and Dixon used a brightness-matching procedure (described in detail by Di Lollo & Finley, 1986) in which luminance was increased for shorter duration stimuli. We instantiated this procedure in our model fit. A fundamental assumption of the model is that increased luminance increases the rate at which information is extracted from a stimulus. Other things being equal, therefore, a higher luminance stimulus will provide more information, and thus better memory performance, than a lower luminance stimulus.

Method

The modified model has five free parameters: n and τ, the parameters of the gamma function used to generate $a(t)$; the preprobe information asymptote; c, which scales the magnitude of $r(t)$; and the postprobe $r(t)$ change factor. For each of Di Lollo and Dixon's (1988) 40 duration–ISI conditions, we generated values for *preprobe* information, *postprobe* information, and *total information*, which is the sum of pre- and postprobe information. We assumed probability correct to be an exponential function of total information. We found the best fit of the model to the data by using a least squares grid-search procedure.

Results

The best fitting parameter values were $n = 2$, $\tau = 97$, $c = 4.1$, asymptote = 0.16, and postprobe $r(t)$ change = 0.36.[3] The results of this procedure are shown in Figure 1, each panel of which shows some variable as a function of duration. The five ISI conditions are 0 ms (open circles), 50 ms (closed circles), 100 ms (open squares), 150 ms (closed squares), and 200 ms (closed triangles).

Adequacy of the model's fit. The bottom right panel shows Di Lollo and Dixon's (1988) data (cf. their Figure 1, p. 674), and the bottom left panel shows the best fitting predicted response probability. At least qualitatively, the model seems to account for the data in the sense of capturing both the inverse-ISI and the inverse-duration effects.

Despite this superficial success, a more detailed examination reveals some serious difficulties. First, the model's quantitative fit to the data is poor. Root-mean-square error is 0.067, which means that on the average, a predicted and observed point differ by almost seven percentage points.

Second, the model–theory deviation is not random as would be expected simply on the basis of noisy data; rather, it is quite systematic. This systematicity is demonstrated in Figure 2, which shows the correlation over the 40 conditions between the data (abscissa values) and the model's predictions (ordinate values). The main diagonal represents a perfect fit of the model to the data. Different symbols represent the different array-duration values. It can be seen that for a set of conditions predicted to be roughly equal (e.g., those that are circled in Figure 2), observed performance is lower with longer durations. This means that the observed inverse-duration effect is greater than the model predicts it to be.

There is an additional model limitation implied by the Figure 2 result. One might argue that perhaps the model's difficulty lies in the specific assumed function (exponential) that relates performance to information. This assumption

[2] The available information function, $a(t)$, that we use in this extension was generated by assuming the kind of linear-system response described in the last section of Loftus, Duncan, and Gehrig with a gamma impulse-response function. See Watson (1986) for details about the nature of linear systems.

[3] That the $r(t)$ change factor is less than 1.0 means that $r(t)$ *decreases* rather than increases following probe presentation. This somewhat nonsensical result is discussed later.

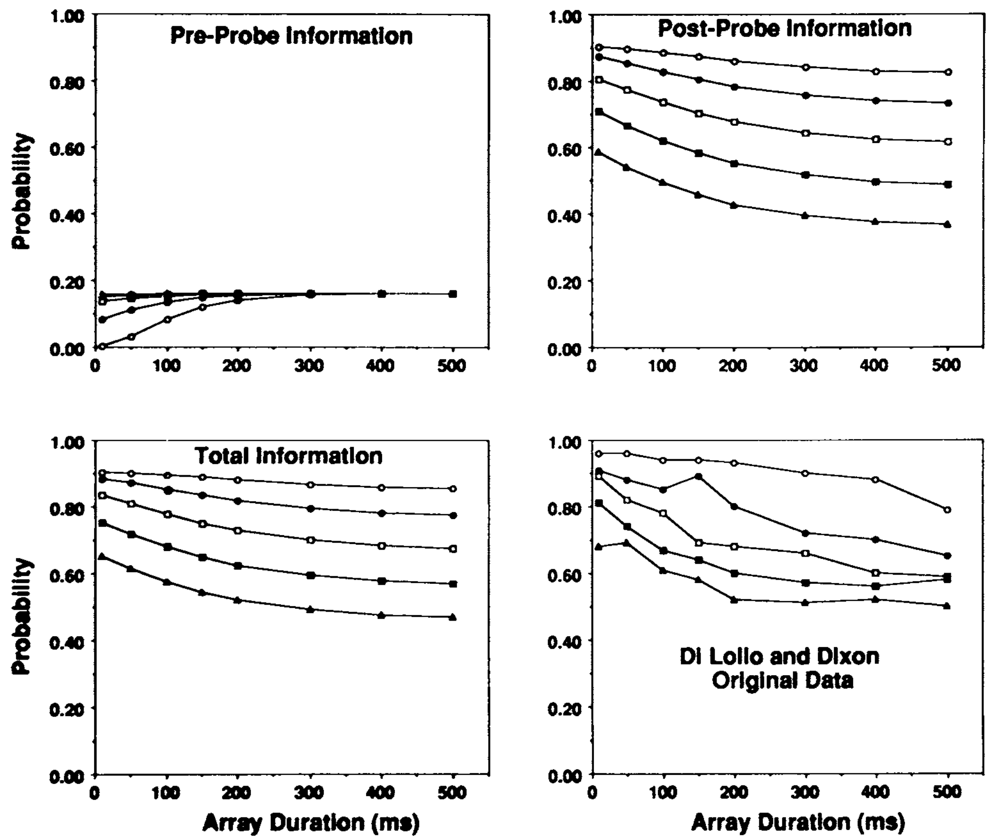

Figure 1. Fit of the extraction-rate model to Di Lollo and Dixon's (1988) data. (Each panel shows some variable as a function of stimulus duration for different interstimulus interval values. Bottom panels show the model's prediction [left] to the data [right]. Top panels show probabilities that are based on preprobe information [left] and postprobe information [right].)

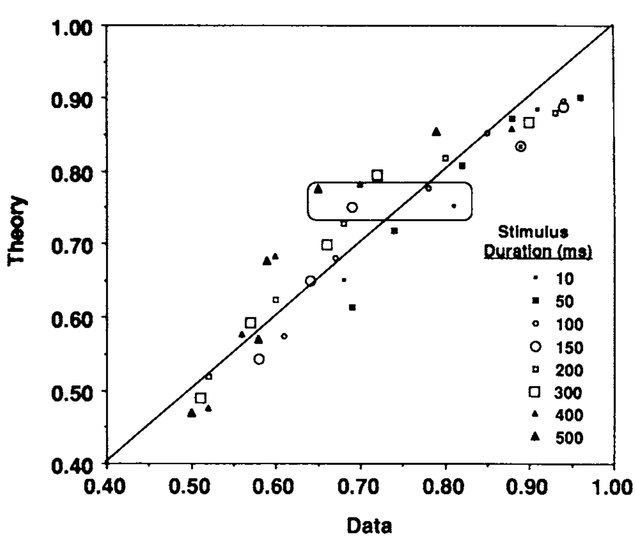

Figure 2. Correlation, over 40 conditions, between model predictions and data. (Different symbols represent different duration values. The 45° line represents perfect prediction. The circled data points illustrate a set of conditions predicted by the extraction-rate model to be roughly equal.)

(discussed in detail in Loftus et al.), although it forms the basis for a useful analytic tool, is not central to the model: Perhaps some other assumed information–performance function would produce a better fit to Di Lollo and Dixon's data. This argument fails, however, because incorporating *any* other monotonic relationship would have the effect of monotonically rescaling the ordinate of Figure 2, which would not change the rank-order correlation. That is, the theory–data relation would remain systematically incorrect.

The model's third difficulty is that the best fitting parameter values are suspect. In particular, the postprobe rate change decreases rather than increases; also, the value of τ is almost twice as great as it was for the Loftus et al. data.[4]

Preprobe information and the nature of the inverse-duration effect. The top left and right panels of Figure 1 show probabilities based on pre- and postprobe information.[5] Inspection

[4] An icon's worth, as defined by Loftus, Duncan, and Gehrig, is roughly equal to $n \times \tau$. This product, computed from the present best fitting parameter values, is almost 200 ms, whereas it was uniformly less than 100 ms in the Loftus, Duncan, and Gehrig data.

[5] As noted, the model actually generates pre- and postprobe *information*, which are added to produce total information that is entered into an exponential equation to produce response probability. For

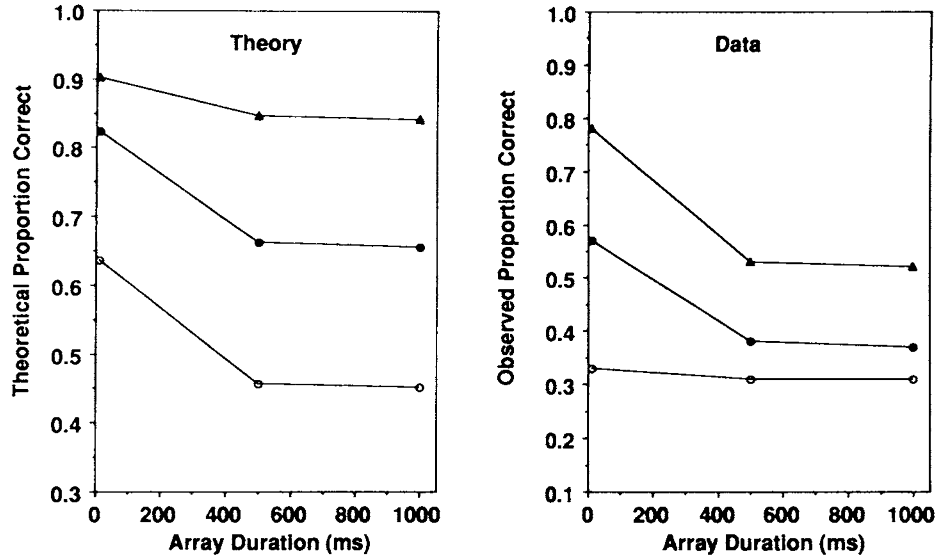

Figure 3. Fit of the extraction-rate model to Di Lollo and Dixon's (1992) data. (The left panel shows the model's prediction, and the right panel shows the data.)

of these panels clarifies why the predicted inverse-duration effect is too small. Preprobe response probability *increases* as a function of duration, whereas postprobe probability correspondingly *decreases*, and the net result is a small decrease. Although not intuitively obvious, it turns out that no combination of parameter values changes this fundamental quality of the model.

It is noteworthy that the postprobe probabilities mirror the Di Lollo and Dixon data better than do the probabilities that are based on total information; the reason is that the former produces a more dramatic inverse-duration effect than the latter. Earlier, we alluded to faulty logic in Loftus and Hanna's application of this model to the same Di Lollo and Dixon data (see Loftus & Hanna's [1989] Figures 13 and 14, pp. 392 and 393). Their error was to assume that partial-report performance was based on postprobe information only.

Application of the Model to Di Lollo and Dixon's (1992) Data

The major difference between Di Lollo and Dixon's (1992) present experimental paradigm and their 1988 paradigm is that in the present paradigm, one of their array durations was very long (1,000 ms). Di Lollo and Dixon argued that Loftus's model would not predict an ISI effect following a 1,000-ms duration. Their reasoning was that at 1,000 ms, the function $r(t)$ would have decayed to zero. Note that this implies a ceiling effect: When the stimulus is still present, $r(t)$ decays to zero only when all stimulus information has been extracted.

comparability, Figure 1 (top panels) depicts probabilities rather than information. These probabilities are computed by entering the information values into exponential equations. A natural interpretation of this scheme is probability summation: A correct response can be made independently on the basis of either type of information.

We used the same parameter values produced by the fit to Di Lollo and Dixon's (1988) data. The results are shown in Figure 3, wherein curves represent the theory predictions (left panel) and the original data (right panel) as functions of array duration. The curves connected with triangles, closed circles, and open circles represents ISIs of 10, 100, and 200 ms.

Several aspects of the fit are noteworthy. First, there is again qualitative correspondence between the data and the model's fit. Second, however, there are some major discrepancies; for example, performance for the two shorter ISIs is predicted to be too high, and the magnitude of the duration effect is greatest at longer ISIs, which is contrary to the data pattern. Third, contrary to Di Lollo and Dixon's assertion, the model's predicted ISI effect following a 1,000-ms array duration is greater, not less, than what was actually observed.

Discussion of the Model Fits

The model fails to account adequately for both sets of Di Lollo and Dixon's data, although not for the reasons delineated by Di Lollo and Dixon in their commentary. Of greatest interest is that the model predicts a strong ISI effect even at long durations. In fairness to Di Lollo and Dixon, we hasten to point out that this ability results from a new assumption about short-term memory limitations. In view of a decades-long tradition of assuming short-term memory to be of limited capacity, however, we do not consider this assumption to be ad hoc. Instead, we consider it to be a natural extension of the model to any experimental situation in which stimulus size exceeds short-term memory capacity.

In light of the relatively good correspondence between the predicted *postprobe* response probabilities and the data (see Figure 1), the model fails as a result of the positive relation between stimulus duration and *preprobe* information. Annoying though it is in the present context, this positive relation cannot be denied; it is precisely this relation that allows the model to predict the extremely robust and pervasive positive relation between stimulus duration and performance in a typical whole-report procedure (e.g., as reported by Loftus et al., 1992).

Despite what we view as the logical and empirical necessity of a positive stimulus-duration–preprobe-information relationship, we note that Di Lollo and Dixon's model assumes no such relationship: Preprobe information is subsumed in the parameter C_0, which is assumed to be constant over all conditions. Although we have not carried out a formal demonstration, we suspect that this feature of Di Lollo and Dixon's model is critical for its ability to account for the inverse-duration effect. In other words, if they assumed some reasonable positive relation between stimulus duration and their C_0, their model would likely run into the same difficulty in accounting for the magnitude of the inverse-duration effect.

Conclusions

The extraction-rate model permits an arbitrary number of informational dimensions. Like Di Lollo and Dixon's model, it requires a mapping of these dimensions onto some unidimensional scale to predict unidimensional performance measures.

The extraction-rate model is capable of accounting for a wide range of data. It cannot, however, quantitatively account for the magnitude of the inverse-duration effect that Di Lollo and Dixon have demonstrated several times. This quantitative failure occurs not for any simple reason, but for complex reasons that are not intuitively obvious.

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