Memory & Cognition
2002, 30 (3), 325-339

Multiple attention systems in perceptual categorization

W. TODD MADDOX
University of Texas, Austin, Texas

and

F. GREGORY ASHBY and ELLIOTT M. WALDRON
University of California, Santa Barbara, California

Five observers categorized inverted L-shaped stimuli according to the length of the horizontal line segment. A centrally located spatial cue preceded the stimulus on each trial. On 80% of the trials, the (relevant) horizontal line segment fell within the cued location, and on 20% of the trials the (irrelevant) vertical line segment fell within the cued location. The empirical results provide support for the hypothesis that perceptual attention can focus on the stimulus attribute inside the spatially cued location at the same time that decisional attention is focused on the (relevant) horizontal attribute—that is, the results suggest that perceptual and decisional attention can function independently during categorization. Decision bound models and extended generalized context models that assume separate perceptual and decisional attention systems were fitted to the data. Versions of the models that assume that the spatial cue affected perceptual attention were superior to versions that assume no effect on perceptual attention. These theoretical analyses support the functional independence hypothesis and suggest that formal theories of categorization should model the effects of perceptual and decisional attention separately.

There is growing consensus that the human attention system is subserved by separate subsystems, or at least by a broad anatomical network in which different subtasks are mediated by different brain areas (e.g., Buchel & Friston, 1997; Knight, 1997; LaBerge, 1997; Olshausen, Anderson, & Van Essen, 1993; Posner & Petersen, 1990; Rushworth, Nixon, Renowden, Wade, & Passingham, 1997). Although a number of different theories have been proposed, there is widespread agreement that visual perceptual attention is mediated by a posterior system that includes the visual cortex, much of the posterior parietal cortex, the pulvinar, and the superior colliculus (e.g., Desimone & Duncan, 1995; Olshausen et al., 1993; Posner & Petersen, 1990). In contrast, executive or decisional (i.e., conscious) attention is thought to be mediated by an anterior system that includes the anterior cingulate, the prefrontal cortex, and perhaps the basal ganglia and the pulvinar (Ashby, Alfonso-Reese, Turken, & Waldron, 1998; Ashby, Isen, & Turken, 1999; Goldman-Rakic, 1995; LaBerge, 1997; Posner & Petersen, 1990). Although anatomically separate, the question of whether the systems are functionally separate has been only recently addressed in the attention literature.

Empirical evidence for a functional independence of perceptual and decisional attention is growing (e.g., Johnston, McCann, & Remington, 1995; Pashler, 1989, 1991, 1993; Posner, 1993; Posner, Sandson, Dhawan, & Shulman, 1989). Johnston et al. (1995) provided some of the strongest evidence to date for the functional independence of perceptual and decisional attention by showing that perceptual and decisional attention systems operate at different temporal stages of processing during letter identification. Specifically, they showed that a critical reference stage of processing (letter identification in their task) operates after the stage of perceptual attention but prior to the stage of decisional attention.

Within the perceptual categorization literature, there is widespread agreement that attentional processes play a prominent role during normal categorization (e.g., Ashby & Lee, 1991; Estes, 1994; Goldstone, 1994; Kruschke, 1992; Maddox, 2002; Maddox & Ashby, 1998; Nosofsky, 1986; Shepard, 1964). However, the question of whether separate perceptual and decisional attention systems operate during categorization has never been broached. One reason for the lack of data that speaks to this question is that no categorization studies have been conducted that have placed the goals of the two systems in direct competition. Rather, the goals of the perceptual and decisional attention systems are usually the same and so, empirically, the actions of the two systems are correlated.

This research was supported in part by National Science Foundation Grants SBR-9796206 and SBR-9514427 and by NIH Grant R01 MH59196. We thank Candace Blair for help with the data collection. We also thank Veronica Black, Evan Heit, Richard Ivry, Robert Nosofsky, Harold Pashler, Jeremy Wolfe, and three anonymous reviewers for helpful comments on an earlier version of this manuscript. Correspondence should be addressed to W. T. Maddox, Department of Psychology, Mezes Hall 330, University of Texas, Austin, TX 78712 (e-mail: maddox@psy.utexas.edu) or to F. G. Ashby, Department of Psychology, University of California, Santa Barbara, CA 93106 (e-mail: ashby@psych.ucsb.edu).

The goal of this article is twofold. First, we describe the results of an experiment in which we investigated whether perceptual and decisional attention can function independently during categorization. The approach combines a traditional categorization task with a popular spatial cuing paradigm (e.g., Eriksen & Hoffman, 1972; Kingstone, 1992; Klein & Hansen, 1987, 1990; McCann, Folk, & Johnston, 1992; Posner, 1980; Posner, Snyder, & Davidson, 1980). Second, we applied decision bound (Ashby, 1992a; Maddox & Ashby, 1993) and extended generalized context models (Lamberts, 1995, 1998) to the data in order to determine the locus of the spatial cuing effect. To anticipate, both the empirical and model-based analyses support the hypothesis that perceptual and decisional attention systems operate separately during categorization. The next (second) section describes the experiment, and the third section outlines the method. The fourth section is devoted to the results and theoretical analyses. Finally, we conclude with some general comments.

SPATIAL CUING IN A PERCEPTUAL CATEGORIZATION EXPERIMENT

To address the functional independence of perceptual and decisional attention in categorization, we combined a categorization task with a spatial cuing manipulation (e.g., Eriksen & Hoffman, 1972; McCann et al., 1992; Posner, 1980; Posner et al., 1980). The basic idea was to devise an experimental task that leads to competition between the perceptual and decisional attention systems on some proportion of trials, but leads to cooperation between the two systems on other trials. Because of the popularity of the spatial cuing paradigm for manipulating perceptual attention, we decided to manipulate perceptual attention processes across trials while holding decisional attention processes fixed. Each stimulus consisted of a vertical and a horizontal line joined at an upper left corner. The lengths of these two line segments varied across trials. The observers were informed prior to the experiment that their task on each trial was to determine whether the horizontal line segment was *short* (Category A) or *long* (Category B) and that the vertical line length was not relevant. Thus, on every trial, the length of the horizontal line was *relevant*, and the length of the vertical line was *irrelevant*, and the goal of the decisional attention system was to place all decisional attention on the horizontal line segment in order to determine whether it was long or short and to place no decisional attention on the vertical line segment. Trial-by-trial feedback was provided to help the observers learn the criterion length that separated short from long horizontal lines. Note that this was not a category learning task in the traditional sense because the observers were told a priori that they should focus decisional attention on the horizontal line segment and that short and long segments belonged in Categories A and B, respectively. Each category contained 11 unique stimuli, which are depicted schematically in Figure 1.

In addition to this standard categorization task, a circular spatial cuing paradigm was used to manipulate perceptual attention on each trial. In many attention tasks that use

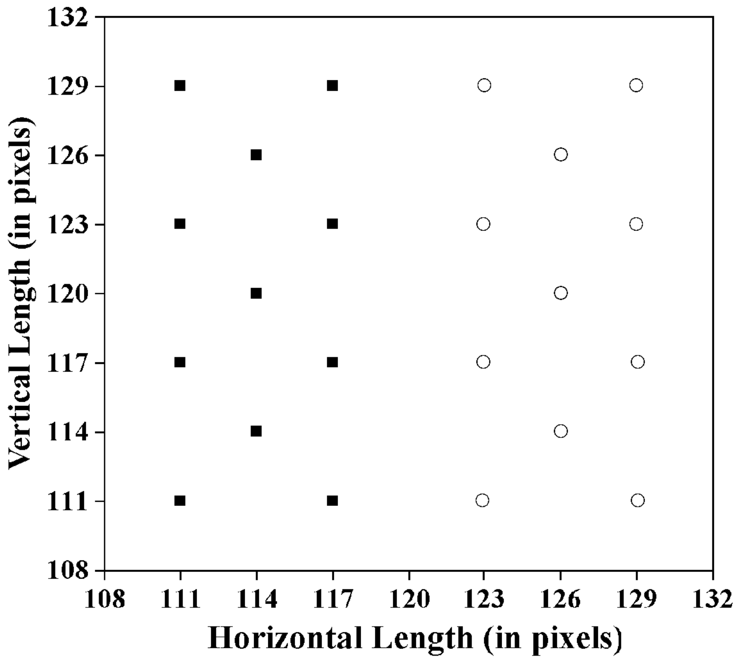

Figure 1. Schematic illustration of the stimulus structure. Solid squares denote stimuli from Category A, and open circles denote stimuli from Category B.

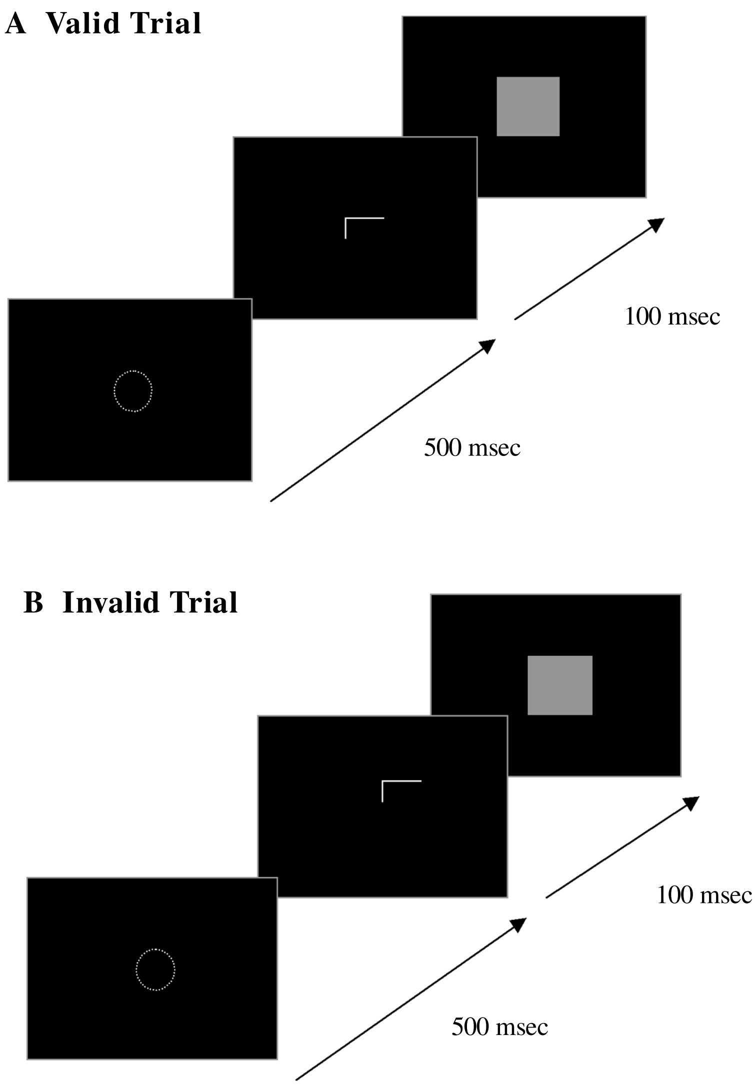

Figure 2. Hypothetical stimulus display for a valid and an invalid trial. The circular attention cue is included for illustrative purposes only and was not present during the stimulus display.

a spatial cue, the cue directs the observer's attention to one of several possible target locations (e.g., Kingstone, 1992; Klein, 1994; Klein & Hansen, 1987, 1990). We took a slightly different approach. On every trial, the circular spatial cue was centered on the computer screen, and the observers were instructed to place all of their perceptual attention within this circular region. The observers were informed that on 80% of the trials, the relevant line segment (i.e., the horizontal line segment) would be displayed within the circular region. We refer to these as *valid trials* because the relevant dimension is presented within the circular region. On the remaining 20% of the trials, the irrelevant line segment (i.e., the vertical line segment) was displayed in the circular region. We refer to these as *invalid trials* because the relevant dimension is presented outside of the circular region.[1] The top panel in Figure 2 depicts a typical valid trial. The circular spatial cue is displayed for 500 msec while the observer allocates perceptual attention to this region. Immediately following the removal of the spatial cue, the stimulus is presented. Because this is a valid trial, the relevant line segment falls within the circular cued region. The stimulus is presented for 100 msec and is then masked. The mask remains on the screen until the observer determines whether the relevant line segment is short or long. The bottom panel in Figure 2 depicts a typical invalid trial. Again the circular spatial cue is displayed for 500 msec while the observer allocates perceptual attention to this region. Immediately following removal of the spatial cue, the stimulus is presented. Because this is an invalid trial, the relevant line segment falls *out-*

side the circular cued region. The stimulus is presented for 100 msec and is then masked. The mask remains on the screen until the observer determines whether the relevant line segment is short or long.

Method

Observers. Five observers participated in the experiment. Each reported 20/20 vision or vision corrected to 20/20. The observers were paid $6.00 per session for their participation.

Stimuli. Each stimulus consisted of a horizontal line and a vertical line connected at the upper left (see Figure 2 for examples). The stimulus ensemble contained 22 stimuli selected from a larger set of 49 stimuli that were constructed from a factorial combination of seven horizontal line lengths with seven vertical line lengths. A schematic of the 22 stimuli is displayed in Figure 1. The seven line lengths were 111, 114, 117, 120, 123, 126, and 129 pixels. The stimuli were computer generated and displayed on a noninterlaced VGA monitor with 1,024 × 768 resolution in a dimly lit room. Each line was presented in white on a black background.

Procedure. The category assignments for the 22 stimuli are depicted in Figure 1. Solid squares denote stimuli from Category A, and open circles denote stimuli from Category B. Each session consisted of five blocks of 110 trials each, for a total of 550 trials. Each of the 22 stimuli was presented five times during each block of trials. During one of the five stimulus presentations (22 trials total), the display of the irrelevant component was centered in the circular cued region (an invalid trial), and during four presentations (88 trials total), the display of the relevant component was centered in the circular cued region (a valid trial). Thus, the spatial cue was 80% valid. During the final three blocks of trials, some of the categorization judgments were followed by an irrelevant component judgment, in which the observer was asked to determine whether the irrelevant component was *short* (less than 120 pixels) or *long* (greater than 120 pixels). The observer was required to make two irrelevant component judgments for each of the 22 stimuli (for a total of 44 irrelevant component judgments per block). One judgment followed a valid trial, and the other followed an invalid trial. No corrective feedback followed the judgments.

Prior to each session, the observers were reminded that the circular spatial cue was valid on 80% of the trials and that they should focus their attention within the circular cued location on each trial. Finally, they were told that they should respond "A" if the horizontal line was shorter than 120 pixels and respond "B" if the horizontal line was longer than 120 pixels. A typical trial proceeded as follows: First, the circular spatial cue was presented for 500 msec centered on the computer screen. The cue was a circle with a diameter of 140 pixels. The cue was replaced by the stimulus that was presented for 100 msec followed by a pattern mask that consisted of a 200 × 200 pixel gray square region. The pattern mask remained on the screen until the observer gave a response. Hypothetical valid and invalid trials are depicted in Figure 2. The observer provided a categorization response, followed by a 500-msec display with corrective feedback and a 500-msec intertrial interval (ITI). When an irrelevant component judgment was required, the 500-msec feedback display was followed by a display that asked for an irrelevant component judgment. The observer provided a response that was followed by a 500-msec ITI and the next trial. No feedback was provided following the irrelevant component judgments. Each observer completed five 1-h sessions on consecutive days. The first session for all observers was considered practice and was excluded from subsequent analyses. The observers were instructed to emphasize accuracy over speed of responding.

Results

All analyses were performed on the data collapsed across Sessions 2–5. We begin with an analysis of the four response types that resulted from the combination of the two dimension judgments [relevant (horizontal) or irrelevant (vertical)] with the two types of spatial cues (valid or invalid). These included (1) judgments of the *relevant* dimension when the spatial cue was *valid* (i.e., when the relevant dimension was in the cued area), (2) judgments of the *relevant* dimension when the spatial cue was *invalid* (i.e., when the relevant dimension was outside of the cued area), (3) judgments of the *irrelevant* dimension when the spatial cue was *valid* (i.e., when the irrelevant dimension was outside of the cued area), and (4) judgments of the *irrelevant* dimension when the spatial cue was *invalid* (i.e., when the irrelevant dimension was in the cued area).

Table 1 displays the proportion of correct responses for each of these four response types averaged across the 22 stimuli separately for each observer. A 2 × 2 within-subjects analysis of variance was conducted on these data. There was a main effect of dimension relevance [$F(1,4) = 29.965$, $p < .005$], with higher accuracy for the relevant (.817) than for the irrelevant component (.623), and no main effect of cue validity. In addition, overall accuracy on the irrelevant component (.623) was above chance ($p < .001$). Finally, the interaction between dimension relevance and cue validity was significant [$F(1,4) = 226.562$, $p < .001$]. A number of additional analyses were conducted in order to isolate the locus of this interaction. Several results stand out. First, accuracy for the relevant dimension was higher on valid trials (.856) than on invalid trials (.778; $p < .02$). Second, relevant dimension accuracy on invalid trials was significantly above chance (i.e., .778; $p < .001$). Third, relevant dimension accuracy on invalid trials (.778) was significantly larger than irrelevant dimension accuracy on invalid trials (.655; $p < .02$). Fourth, irrelevant component accuracy was higher on invalid trials (.655) than on valid trials (.591; $p < .06$). Finally, irrelevant component accuracy on invalid trials (i.e., .655) was significantly lower than relevant component accuracy on valid trials (i.e., .856; $p < .005$).[2]

Taken together, these results provide initial support for functional independence of perceptual and decisional attention in categorization and suggest that decisional attention can make use of information that is not facilitated by the spatial cue. If the perceptual and decisional attention systems are yoked, then on invalid trials, when the irrelevant dimension is in the cued location, no information regarding the relevant dimension should be available for processing, and relevant dimension performance should be at

Table 1
Overall Proportion Correct

	Relevant		Irrelevant	
Observer	Valid	Invalid	Valid	Invalid
1	.910	.840	.690	.745
2	.890	.840	.475	.590
3	.820	.720	.580	.635
4	.850	.690	.610	.565
5	.810	.800	.600	.740
Average	.856	.778	.591	.655

chance. If, on the other hand, the perceptual and decisional attention systems are functionally independent, the decisional attention system will be focused on the relevant dimension, even when perceptual attention is focused on the irrelevant dimension (as is true on an invalid trial), and performance will be above chance. It is worth mentioning that all of these results, based on averaged data, hold for each individual observer. Specifically, for every observer, relevant component accuracy on valid trials was higher than relevant component accuracy on invalid trials and higher than irrelevant component accuracy on invalid trials. For 4 of the 5 observers, irrelevant component accuracy was higher on invalid trials than on valid trials. Also, overall accuracy on the relevant component was significantly higher than overall accuracy on the irrelevant component.[3]

Figure 3 displays the proportion of correct responses for the relevant component for each of the 22 stimuli on valid (i.e., top panel) and invalid (i.e., bottom panel) trials averaged across the 5 observers using the same spatial configuration of stimuli depicted in Figure 1. Figure 4 displays the same proportions for the relatively few trials in which the observers were asked to judge the length of the irrelevant component. For both the relevant and irrelevant judgments, and for both cue validity conditions, the accuracy of all responses increased with the distance from the stimulus to the category decision bound. This finding is especially informative with regard to the irrelevant component accuracy, because it indicates that the decisional attention system had some access to the irrelevant component. However, it is impossible to tell from these analyses whether information about the irrelevant component was available at the same time that the decisional attention system was judging the length of the relevant component, or whether decisional attention was switched to the irrelevant component after the relevant component judgment was completed.

A closer examination of the stimulus-by-stimulus accuracy rates in Figures 3 and 4 suggests that the decisional attention system was not able to set a criterion perfectly along the relevant dimension while ignoring the irrelevant dimension. Specifically, the relevant dimension accuracy rates for stimuli from the *short* category (i.e., with hori-

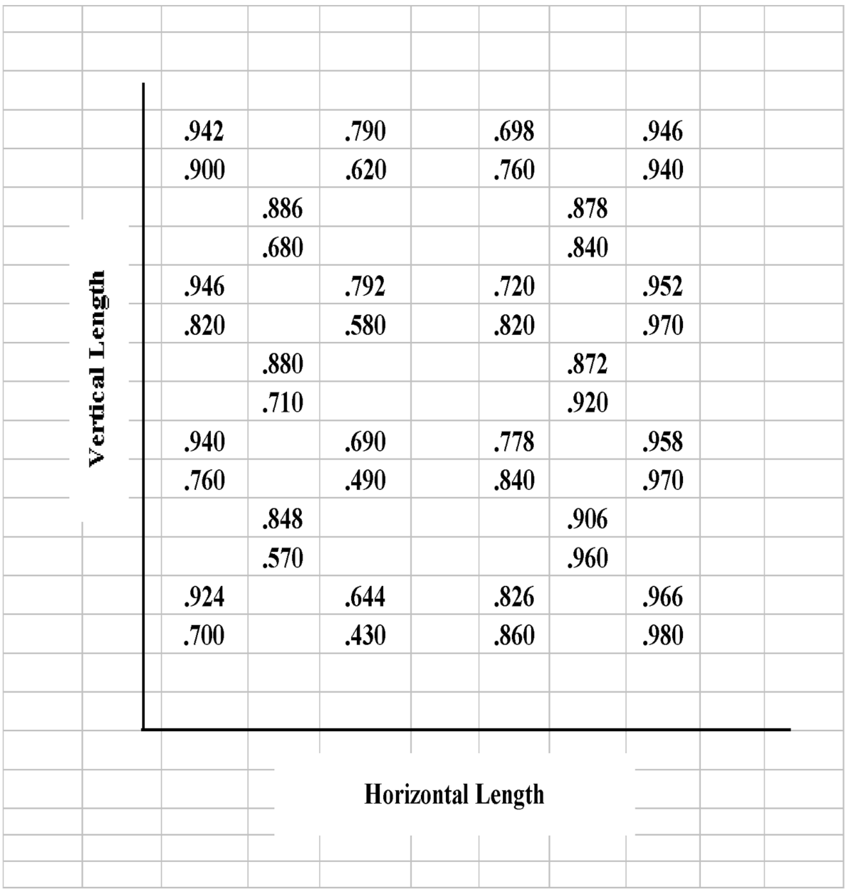

Figure 3. Correct categorization proportions for the relevant component averaged across the 5 observers. The top value of each pair denotes the proportion correct on valid trials, and the bottom value of each pair denotes the proportion correct on invalid trials.

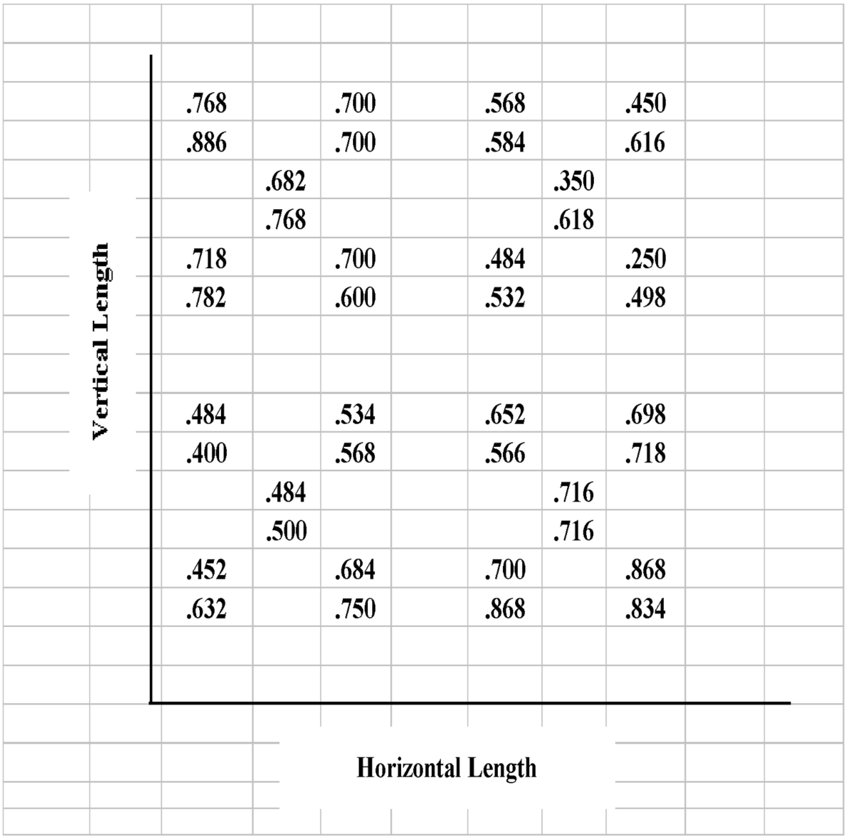

Figure 4. Correct categorization proportions for the irrelevant component averaged across the 5 observers. The top value of each pair denotes the proportion correct on valid trials, and the bottom value of each pair denotes the proportion correct on invalid trials.

zontal lengths less than 120 pixels) generally increased with increasing vertical length, whereas the accuracy rates for stimuli from the *long* category (i.e., with horizontal lengths greater than 120 pixels) generally decreased with increasing vertical length. A similar result held for the irrelevant dimension judgments. Specifically, the accuracy rates for stimuli from the *short* category (i.e., with vertical lengths less than 120 pixels) generally increased with increasing horizontal length, whereas the accuracy rates for stimuli from the *long* category (i.e., with vertical lengths greater than 120 pixels) generally decreased with increasing horizontal length. This finding was not completely unexpected since these stimulus dimensions were measured in the same units and likely had some *integral-dimension* qualities that made it difficult for the decisional attention system to ignore completely the irrelevant dimension (e.g., Garner, 1974; Maddox, 1992).

THEORETICAL ANALYSES

The results so far support the hypothesis that the perceptual and decisional attention systems can function separately in perceptual categorization, but this inference relies on the assumption that the observers placed all of their perceptual attention within the cued region. A more reasonable assumption is that some perceptual attention spills out of the cued circular region, even when the cuing instructions are effective. In this case, testing whether perceptual and decisional attention can function independently and determining the locus of the attention effect is difficult, in the sense that it requires a process of parameter estimation and model fitting. In this section, we examine the functional independence of perceptual and decisional attention in two different but successful models of categorization: Ashby and Maddox's (1993; Maddox & Ashby, 1993) *decision bound model* (DBM), and Lamberts's (1995, 1998) *extended generalized context model* (EGCM). Nosofsky's (1986) *generalized context model* (GCM) is not examined below, because it does not separate perceptual from decisional attention (instead it assumes a unitary attention system; Maddox & Ashby, 1998), and because it is rejected in favor of the other models for every observer.

Decision Bound Theory

Decision bound theory takes as its fundamental axiom that all perceptual systems are probabilistic—that is, repeated presentations of the same stimulus yield different

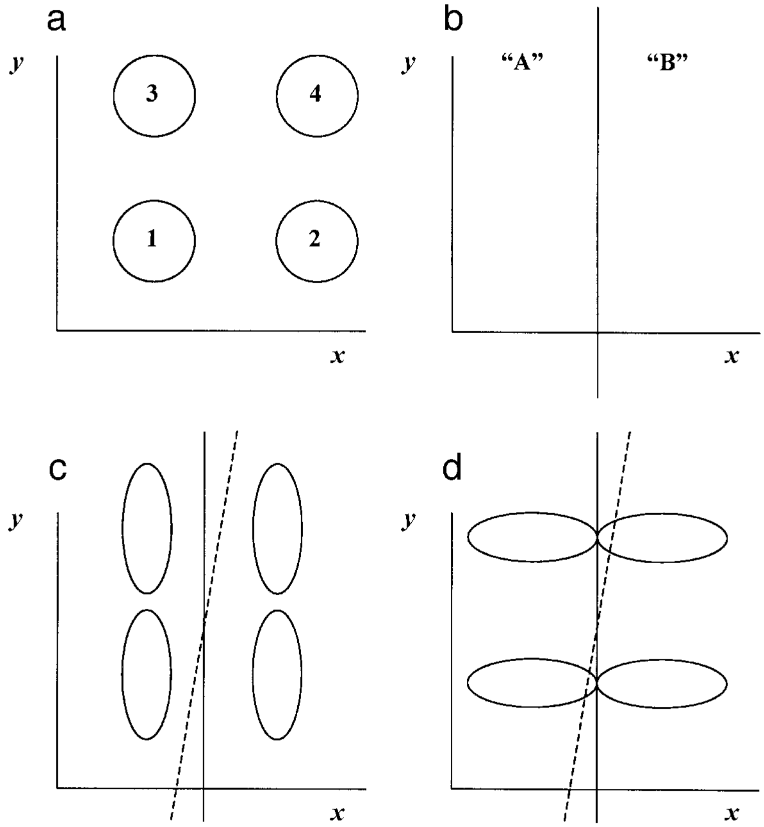

Figure 5. (a) Hypothetical contours of equal likelihood for four stimuli (1–4). (b) Hypothetical decision bound for a categorization problem in which Stimuli 1 and 3 are members of Category A and Stimuli 2 and 4 are members of Category B. (c) Hypothetical contours of equal likelihood for a case in which there is perceptual selective attention to dimension *x*. The solid line decision bound depicts a case in which decisional selective attention to dimension *x* is perfect, and the dashed line depicts a case in which decisional selective attention to dimension *x* is imperfect. (d) Hypothetical contours of equal likelihood for a case in which there is perceptual selective attention to dimension *y*. The solid line decision bound depicts a case in which decisional selective attention to dimension *x* is perfect, and the dashed line depicts a case in which decisional selective attention to dimension *x* is imperfect.

perceptual effects (e.g., Ashby & Lee, 1993; Geisler, 1989; Green & Swets, 1967). The *perceptual noise* elicited by repeated presentations of a single multidimensional stimulus can be represented by a multivariate probability distribution (Ashby & Lee, 1993). For a two-dimensional stimulus, a bivariate normal distribution is assumed to describe the set of percepts. A bivariate normal distribution is described by a mean and variance along each dimension, as well as a covariance term, μ_x, μ_y, σ_x^2, σ_y^2, cov_{xy}, where the subscripts x and y denote dimensions x and y. Figure 5a depicts hypothetical equal likelihood contours for four stimuli constructed from the factorial combination of two levels along two dimensions x and y. With bivariate normal distributions, the equal likelihood contours are always circular or elliptical. When the major and minor axes of the contour are parallel to the coordinate axes, the covariance (correlation) is zero. All four distributions in Figure 5a have zero covariance. A positive slope for the major axis implies a positive covariance (correlation), and a negative slope implies a negative covariance. The greater the variance along a dimension, the wider the contour in that direction.

In decision bound theory, the experienced observer learns to divide the perceptual space into response regions and assigns a response to each region. On each trial, the observer determines the location of the perceptual effect and gives the response associated with that region of the perceptual space. The partition between response regions is called the *decision bound*. Figure 5b displays a hypothetical decision bound for a categorization task in which Stimuli 1 and 3 are placed in Category A, and Stimuli 2 and 4 are placed in Category B. Note that the parameters that define the perceptual representation are separate from the parameters that define the decision bound (Ashby, 1992a).

In decision bound theory, perceptual attention is assumed to affect the perceptual variances, and decisional attention is assumed to affect the decision bounds. In particular, perceptual attention is assumed to reduce the trial-by-trial variability in the perceived values of a stimulus along the perceptually attended dimension, relative to the variability along the perceptually unattended dimension (Braida & Durlach, 1972; Durlach & Braida, 1969; Luce & Green, 1978; Luce & Nosofsky, 1984; Macmillan, Goldberg, & Braida, 1988). Figure 5c depicts a situation in which more perceptual attention is directed to dimension x than to dimension y. This reduces the perceptual noise along dimension x relative to the perceptual noise along dimension y. Figure 5d depicts a situation in which perceptual attention is directed more to dimension y. Thus, decision bound theory can be used to test the hypothesis that some perceptual attention spills out of the cued circular region. If this is the case, then on valid trials, the perceptual variance of the irrelevant component (which falls outside the cued circular region) will be some finite value.

Decisional selective attention results when the decision bound is orthogonal to one of the coordinate axes—that is, when the observer sets a criterion along one stimulus dimension and places no decisional attention on the other dimension. This decision strategy is also referred to as *decisional separability* (see Ashby & Townsend, 1986, and Maddox, 1992, for details). Decisional selective attention to dimension x holds in both Figures 5c and 5d, as denoted by the solid line decision bound. Like perceptual selective attention, the magnitude of decisional selective attention can vary. For example, the broken line decision bounds in Figures 5c and 5d depict cases in which there is imperfect decisional selective attention to dimension x. Note that in Figure 5c both attention systems, perceptual and decisional, are operating on the same stimulus dimension x. In Figure 5d, on the other hand, there is perceptual selective attention to dimension y, but decisional selective attention to dimension x. Taken together, panels c and d of Figure 5 demonstrate pictorially that perceptual and decisional attention processes are separate and thus that a functional independence, if it exists, can be isolated.

Decision bound models. To test whether perceptual and decisional attention can function independently, we fit decision bound models to the relevant (i.e., horizontal) line length judgments for each of the 22 stimuli separately for each individual observer. We did not fit the irrelevant line length judgments because of the small number of these judgments. For each stimulus, we computed the observed probability of responding "short" and the observed probability of responding "long" for both valid and invalid trials. Thus, each model was fit to a total of 88 estimated response probabilities from each observer. The model yielded predicted probabilities of responding "short" and "long" for both valid and invalid trials by solving the following equations:

$$P(\mathbf{R}_{\text{short}} \mid \mathbf{x}_i) = P[h(\mathbf{x}_{pi}) < 0 \mid \mathbf{x}_i]$$

$$P(\mathbf{R}_{\text{long}} \mid \mathbf{x}_i) = 1 - P(\mathbf{R}_{\text{short}} \mid \mathbf{x}_i),$$

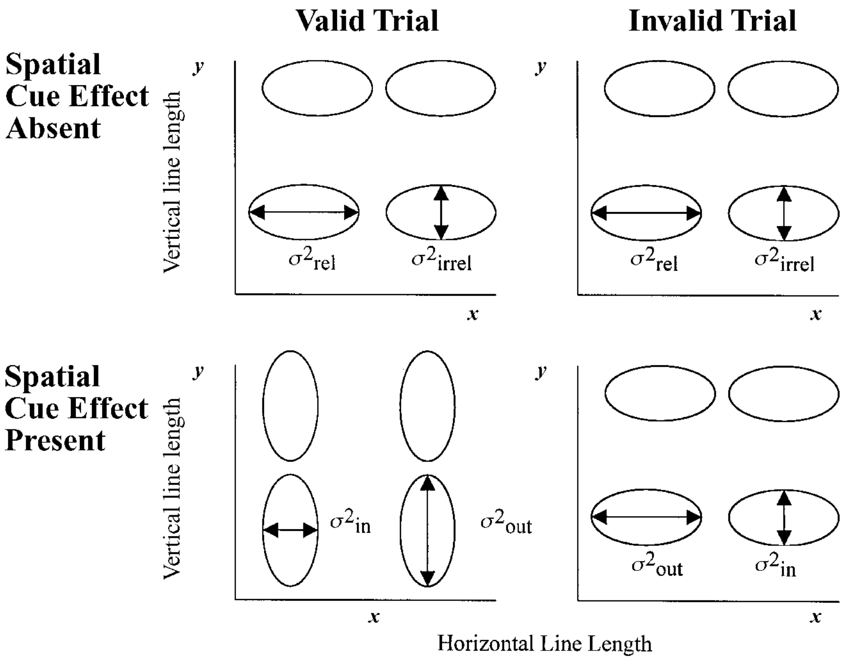

Figure 6. Schematic illustration of the two hypotheses on the effect of the spatial cue on perceptual attention. The left column depicts valid trials, and the right column depicts invalid trials. The top portion depicts the case in which there is no spatial cue effect on perceptual attention (labeled Spatial Cue Effect Absent), and the bottom portion depicts the case in which there is a spatial cue effect on perceptual attention (labeled Spatial Cue Effect Present). (See text for details.)

where $\boldsymbol{x}_i$ is a vector that contains the horizontal and vertical lengths for stimulus i, $\boldsymbol{x}_{pi}$ is the perceptual effect for stimulus i under the assumption that bivariate normal perceptual noise exists, and h is a linear decision function (i.e., the equation for a linear decision bound). Decision bound theory also postulates noise in the decision process—that is, criterial noise. However, when the decision bound is linear, as in the present application, criterial noise is nonidentifiable with perceptual noise.

Four decision bound models were tested. They were constructed by combining factorially two hypotheses regarding the effects of the spatial cue on the perceptual variances with two hypotheses regarding the effects of the spatial cue on the decision bounds. The two hypotheses regarding the effects of the spatial cue on perceptual attention are depicted in Figure 6. One hypothesis assumes no effect of the spatial cue on the perceptual variances and is displayed in the top two panels of Figure 6 (labeled Spatial Cue Effect Absent). This hypothesis requires that two perceptual variance parameters be estimated from the data. One represents the perceptual variance along the relevant dimension (regardless of cue validity), and the other represents the perceptual variance along the irrelevant dimension (regardless of cue validity). The second hypothesis assumes that the spatial cue had an effect on the perceptual variances and is displayed in the bottom two panels of Figure 6 (labeled Spatial Cue Effect Present). This hypothesis also requires two perceptual variance parameters. However, in this case, the perceptual parameters are not linked to the relevant and irrelevant dimensions but rather to which dimension was presented inside or outside of the spatial cue. Specifically, one perceptual variance was estimated for the component inside the spatial cue (i.e., the relevant dimension on valid trials, and the irrelevant dimension on invalid trials). A second perceptual variance was estimated for the component outside of the spatial cue (i.e., the irrelevant dimension on valid trials, and the relevant dimension on invalid trials).[4]

A similar pair of hypotheses was made about the effects of decisional attention on the decision bound. The two hypotheses regarding the effects of the spatial cue on decisional attention are depicted in Figure 7. One hypothesis assumes no effect of the spatial cue on the decision bound—that is, that the same (linear) decision bound was used on

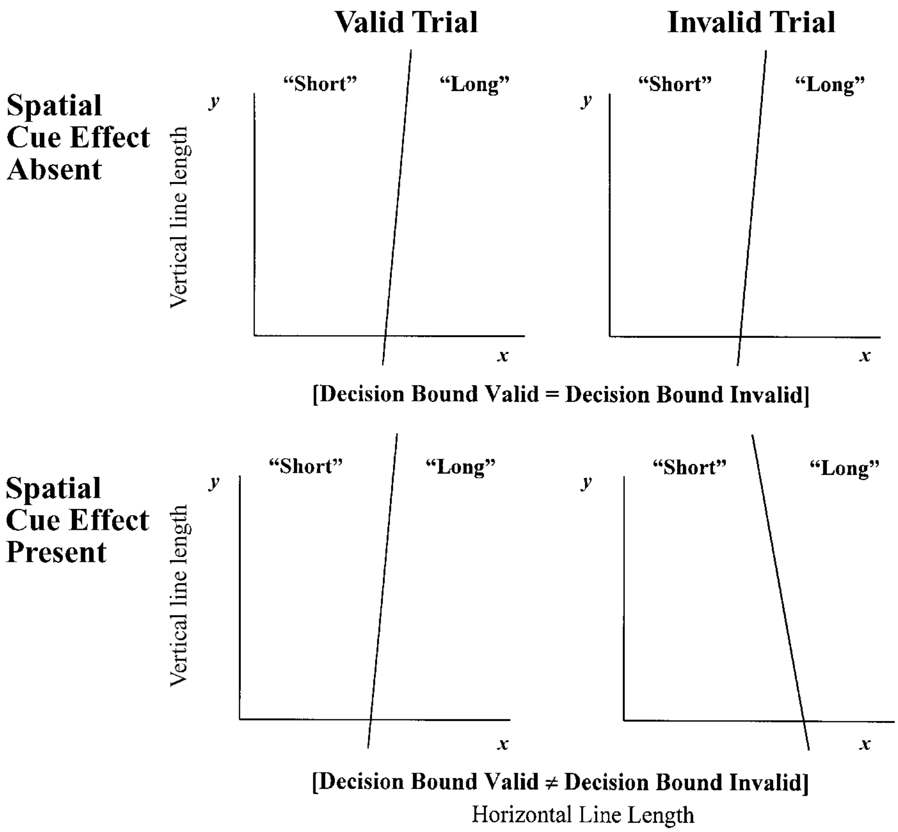

Figure 7. Schematic illustration of the two hypotheses on the effect of the spatial cue on decisional attention. The left column depicts valid trials, and the right column depicts invalid trials. The top portion depicts the case in which there is no spatial cue effect on decisional attention (labeled Spatial Cue Effect Absent), and the bottom portion depicts the case in which there is a spatial cue effect on decisional attention (labeled Spatial Cue Effect Present). (See text for details.)

valid and invalid trials. (Quadratic decision bounds were also examined but in no case provided a significant improvement in fit.) This situation is depicted in the top portion of Figure 7 (labeled Spatial Cue Effect Absent). This version adds two free decision bound parameters (i.e., the slope and the intercept of the bound used on all trials). The second hypothesis was that the spatial cue affected the decision bound. In this case, different linear decision bounds were applied on valid and invalid trials (resulting in four bound parameters—the slope and the intercept of the bound used on valid trials, and the slope and the intercept of the bound used on invalid trials). This situation is depicted in the bottom portion of Figure 7 (labeled Spatial Cue Effect Present). The resulting four models are designated as follows.

Model DBM(•,•). The spatial cue has no effect on perceptual variability or on the decision bound (i.e., the cue has no effect on perceptual or decisional attention). This model has four free parameters: two perceptual variance parameters (see Figure 6, top panels), and two decision bound parameters (see Figure 7, top panels).

Model DBM(P,•). The spatial cue affects the perceptual variances but not the decision bound (i.e., the cue affects perceptual attention but not decisional attention). This model has four free parameters: two perceptual variance parameters (see Figure 6, bottom panels), and two decision bound parameters (see Figure 7, top panels).

Model DBM(•,D). The spatial cue affects the decision bound but not the perceptual variances (i.e., the cue affects decisional attention but not perceptual attention). This model has six free parameters: two perceptual variance parameters (see Figure 6, top panels), and four decision bound parameters (see Figure 7, bottom panels).

Model DBM(P,D). The spatial cue affects the perceptual variances and the decision bound (i.e., the cue affects perceptual and decisional attention). This model has six free parameters: two perceptual variance parameters (see Figure 6, bottom panels), and four decision bound parameters (see Figure 7, bottom panels).

Each of these models was fitted to the relevant component data separately for each observer. The model parameters were by estimated using maximum likelihood (Ashby, 1992b; Wickens, 1982) and the goodness-of-fit statistic was $-\ln L$, where L is the likelihood of the model given the data.

The goodness-of-fit values ($-\ln L$) for each model and observer are presented in Table 2. The fit of the most parsimonious decision bound model for each observer is in bold type. The results can be summarized as follows: First, the spatial cue had the predicted effect on perceptual attention. For all 5 observers, the model that assumes the cue affected perceptual attention fit better than the corresponding model that assumes no effect of the cue on perceptual attention [i.e., DBM(P,•) always fit better than DBM(•,•), and DBM(P,D) always fit better than DBM(•,D)], even though the two models had the same number of perceptual variance parameters. Second, also as predicted, in the best-fitting model, the perceptual variance for the component within the spatial cue (average SD = 4.936) was smaller than the perceptual variance for the component outside of the spatial cue (average SD = 5.806) for 4 of the 5 observers ($p < .05$). The exact values are displayed in Table 3. This was true regardless of whether the relevant or irrelevant component was within the spatial cue. Thus, perceptual attention was focused on the component within the spatial cue. Third, in 9 of 10 comparisons, the model that assumes that the cue affected decisional attention fit better than the corresponding model that assumes no effect of the cue on decisional attention [i.e., DBM(•,D) always fit better than DBM(•,•), and DBM(P,D) fit better than DBM(P,•) for 4 of the 5 observers]. To determine the magnitude of the spatial cue effect on the observer's ability to apply decisional selective attention, the "weight" given to each component in the categorization decision was determined by examining the slope of the best-fitting linear decision bound. A slope of zero implies that all weight was given to the irrelevant component and that none was give to the relevant component (i.e., decisional selective attention to the irrelevant component). A slope of one implies that equal weight was given to both the irrelevant and relevant components, and an infinite slope implies decisional selective attention to the relevant component. Not surprisingly, on invalid trials, the irrelevant component was given greater weight in the categorization decision than it was given on valid trials [i.e., in model DBM(P,D)]. Even so, on both valid and

Table 2
Goodness-of-Fit ($-\ln L$) Values for the Decision Bound and Extended Generalized Context Models

	Decision bound Models				Extended Generalized Context Models			
Observer	DBM(•,•)	DBM(P,•)	DBM(•,D)	DBM(P,D)	EGCM(•,•)	EGCM(P,•)	EGCM(•,D)	EGCM(P,D)
	(4 parm)	(4 parm)	(6 parm)	(6 parm)	(5 parm)	(5 parm)	(6 parm)	(6 parm)
1	654.13	**644.06**	643.72	643.71	665.18	660.58	657.13	**657.12**
2	764.29	754.62	702.88	**702.46**	761.86	**756.45**	757.26	756.35
3	938.09	935.87	926.10	**922.31**	942.46	934.94	931.21	**931.11**
4	873.77	865.01	781.26	**780.56**	936.98	916.17	906.30	**906.30**
5	978.74	978.63	974.17	**974.08**	988.60	**988.46**	988.48	988.38
Average	841.80	835.64	805.63	804.62	859.01	851.32	848.08	847.85

Note—The values in bold type denote the most parsimonious model from each model class (decision bound or extended generalized context).

Table 3
Perceptual Noise Standard Deviation Inside and Outside of the Spatial Cue for the Best-Fitting Decision Bound Model

	Spatial Cue	
Observer	Inside	Outside
1	3.793	5.389
2	4.309	4.613
3	5.712	7.543
4	4.653	5.312
5	6.211	6.172
Average	4.936	5.806

invalid trials, the decision bounds of all observers weighted the relevant component much more heavily than the irrelevant component (i.e., the slopes were all much larger than one). Thus, although the decisional attention system allocated some attention to the irrelevant component (for Observers 2–5), the lion's share of decisional attention was focused on the relevant component, regardless of whether it was inside or outside of the spatial cue. This result was expected, since Figures 3 and 4 suggest that some decisional attention was focused on the irrelevant component. Finally, for 4 of the 5 observers, the best fit was provided by model DBM(P,D), which is strong evidence that the cue affected both perceptual and decisional attention.

Extended Generalized Context Model

Unlike decision bound theory, the *extended generalized context model* (EGCM) assumes no perceptual noise and that each stimulus is represented by a point in a multidimensional psychological space. When presented with a target stimulus, the observer computes the distance from the target item to each category exemplar stored in memory. Each distance is then converted into a similarity as follows:

$$\eta_{ij} = \exp\{-c\,[\mathrm{inc}_h u\,|h_i - h_j|^r + \mathrm{inc}_v(1-u)\,|v_i - v_j|^r]^{q/r}\},$$

where η_{ij} denotes the similarity between stimuli i and j, c is a scaling constant, inc_h is the binary valued (0 or 1) inclusion probability for the horizontal component, inc_v is the binary valued inclusion probability for the vertical component, and u is the utility placed on the horizontal component ($0 < u < 1$; $\Sigma u = 1$). Following most applications of the model to continuous-valued stimuli, we assume Euclidean distance ($r = 2$) and an exponential decay similarity function ($q = 1$). Lamberts (1995, 1998) has suggested that the inclusion probabilities are affected by perceptual processes and that the utility value is affected by the decision process. The probability of responding "short" for both valid and invalid trials is determined from the following equation:

$$P(\mathbf{R}_{\mathrm{short}}|x_i) = \frac{\beta_{\mathrm{short}} \sum_{j \in \mathrm{short}} \eta_{ij}}{\beta_{\mathrm{short}} \sum_{j \in \mathrm{short}} \eta_{ij} + \beta_{\mathrm{long}} \sum_{j \in \mathrm{long}} \eta_{ij}},$$

where β_{short} is the bias toward responding "short" ($\beta_{\mathrm{long}} = 1 - \beta_{\mathrm{short}}$), and the $P(\mathbf{R}_{\mathrm{long}}|x_i) = 1 - P(\mathbf{R}_{\mathrm{short}}|x_i)$. Because the inclusion probabilities are binary valued, perceived similarity changes discretely across time and trial. Since we are fitting the model to aggregate data, the probability of each possible inclusion pattern (i.e., neither component, horizontal component only, vertical component only, both components) is computed from continuous-valued inclusion probabilities, i_1 and i_2, that are estimated from the data and can take on any value between 0 and 1. For each stimulus, x_i, the choice probability for each inclusion pattern is computed, and the expected value of these choice probabilities denotes the model prediction (see Lamberts, 1998, for details).

Four extended generalized context models were tested. They were constructed by combining factorially two hypotheses regarding the effects of the spatial cue on the inclusion probabilities, i, with two hypotheses regarding the effects of the spatial cue on the utility parameter, u.

Model EGCM(•,•). The spatial cue has no effect on the inclusion probabilities or on the utility (i.e., the cue has no effect on perceptual or decisional attention). This model has five free parameters: c, i_h, i_v, u, and β.

Model EGCM(P,•). The spatial cue affects the inclusion probabilities with one inclusion probability applying to the component within the spatially cued location (i.e., the relevant, horizontal component on valid trials, and the irrelevant, vertical component on invalid trials) and a second inclusion probability applying to the component outside of the spatially cued location (i.e., the relevant component on invalid trials, and the irrelevant component on valid trials). The spatial cue does not affect the utility. This model has five free parameters: c, i_{inside}, i_{outside}, u, and β.

Model EGCM(•,D). The spatial cue has no effect on the inclusion probabilities, but does affect the utility with one utility for valid trials and a second utility for invalid trials. This model has six free parameters: c, i_h, i_v, u_{valid}, u_{invalid}, and β.

Model EGCM(P,D). The spatial cue affects the inclusion probabilities and the utilities. This model has six free parameters: c, i_{inside}, i_{outside}, u_{valid}, u_{invalid}, and β.

The goodness-of-fit values ($-\ln L$) for each model and observer are presented in Table 2. The fit of the most parsimonious EGCM is in bold type.[5] The results can be summarized as follows: First, the spatial cue had the predicted effect on perceptual attention. For all 5 observers, the model that assumes the cue affected the inclusion probabilities fit as well or better than the corresponding model that assumes no effect of the cue on perceptual attention [i.e., EGCM(P,•) compared with EGCM(•,•), and EGCM(P,D) compared with EGCM(•,D)]. Second, also as predicted, in the EGCM(P,•), the inclusion probability for the component within the spatial cue (average $i_{\mathrm{inside}} = .999$) was larger than the inclusion probability for the component outside of the spatial cue (average $i_{\mathrm{outside}} = .820$) for all 5 observers ($p < .05$). The exact values are displayed in Table 4. Thus, perceptual attention was fo-

Table 4
Inclusion Probabilities Inside and Outside of the Spatial Cue for the EGCM(P,•)

	Spatial Cue	
Observer	Inside	Outside
1	1.000	.889
2	.999	.875
3	.999	.749
4	.998	.607
5	.999	.982
Average	.999	.820

cused on the component within the spatial cue. Third, in 7 of 10 cases, the model that assumes the cue affected decisional attention fit significantly better (based on likelihood ratio tests) than the corresponding model that assumes no effect of the cue on decisional attention [i.e., EGCM(•,D) compared with EGCM(•,•), and EGCM(P,D) compared with EGCM(P,•)]. To determine the magnitude of the spatial cue effect on the observer's ability to apply decisional selective attention, the utility value from the EGCM(•,D) was examined. For all 5 observers, the utility for the relevant component was larger on valid (average $u_{\text{valid}} = .759$) than on invalid (average $u_{\text{invalid}} = .436$) trials ($p < .05$). Finally, the best fit was provided by the EGCM(P,•) for 2 observers and by the EGCM(P,D) for the other 3 observers.

Comparison of Decision Bound and Extended Generalized Context Models

In 8 of 10 cases, the decision bound model that assumes no effect of the spatial cue on decisional attention [i.e., DBM(•,•) and DBM(P,•)] provided a better account of the data than did the analogous extended generalized context model [i.e., EGCM(•,•) and EGCM(P,•)]. Similarly, in 10 of 10 cases, the decision bound model that assumes an effect of the spatial cue on decisional attention [i.e., DBM(•,D) and DBM(P, D)] provided a better account of the data than did the analogous extended generalized context model [i.e., EGCM(•,D) and EGCM(P, D)]. To shed additional light on the ability of the two models to account for the data, we computed the absolute deviation between the predicted and the observed probabilities of responding "A" for the relevant segment for each of the 22 stimuli on both valid and invalid trials. We then computed the average across the 22 stimuli on valid trials and the average across the 22 stimuli on invalid trials. We computed these two values for each observer for the DBM(P,D) and EGCM(P,D) models. These data are presented in Table 5. Several comments are in order. First, note that both models provided a better account of the valid trial data than the invalid trial data, and the performance of the two models were more similar for the valid trials. Even so, for valid trials, the DBM model predictions are closer to the observed values than are the EGCM model predictions for all 5 observers. Second, note that the decision bound model provides a better account of invalid trial data for all 5 observers.

Irrelevant component judgments. Neither model was fit to the irrelevant component judgments because of the small amount of data. Even so, both models provide good qualitative accounts of these data by assuming that the perceptual variance for the component inside the spatial cue was smaller than the perceptual variance for the component outside of the spatial cue, for the decision bound model, and by assuming that the inclusion probabilities inside the spatial cue were larger than those outside of the spatial cue, for the EGCM. Of course, the accuracy of quantitative fits of these models awaits further research.

SUMMARY AND CONCLUSIONS

This article reports the results of an experiment that provides a test of two hypotheses regarding the nature of perceptual and decisional attention during perceptual categorization. One hypothesis is that perceptual and decisional attention are yoked, and the other is that perceptual and decisional attention are functionally independent. To test these hypotheses, we combined a traditional perceptual categorization task with a spatial cuing manipulation (e.g., Eriksen & Hoffman, 1972; Posner, 1980). The goal of the decisional attention system was to judge the length of a horizontal line segment. On valid trials, the horizontal line segment fell within the spatially cued region, and on invalid trials, the horizontal line segment fell outside of the spatially cued region. Thus, on valid trials, the two systems were able to work in concert, and on invalid trials, the two systems competed. If the two attention systems are yoked, performance should be at chance on invalid trials and well above chance on valid trials. On the other hand, if the two attention systems are functionally independent, performance should be above chance on both valid and invalid trials, although valid trial performance should be superior.

The accuracy and theoretical analyses support the hypothesis that perceptual and decisional attention can function independently in categorization. Specifically, the two systems can operate with different goals, in which one system focuses attention on one stimulus component at the same time the other system is focusing attention on a

Table 5
Average Absolute Deviation Between Predicted and Observed Response Probabilities for DBM(P,D) and EGCM(P,D)

	DBM(P,D)		EGCM(P,D)	
Observer	Valid	Invalid	Valid	Invalid
1	.016	.047	.029	.058
2	.029	.048	.034	.151
3	.037	.059	.042	.081
4	.028	.039	.087	.186
5	.027	.055	.042	.089
Average	.027	.050	.047	.113

different component. This conclusion validates current work in cognitive neuroscience that has attempted to map out a variety of separate, but interconnected, attention systems (e.g., perceptual, decisional, vigilance; Posner & Petersen, 1990). It also points to the need to model perceptual and decisional attention separately in formal models of categorization.

Although we argue that the most reasonable interpretation of these results is in support of the functional independence hypothesis, one might be able to develop a single-system exemplar model that could account for these data. For example, one could assume that, on every trial, the observers distribute their unitary attention to the four following locations: (1) the likely location of the endpoint of the horizontal line on a valid trial, (2) the likely location of the endpoint of the horizontal line on an invalid trial, (3) the likely location of the endpoint of the vertical line on an invalid trial, and (4) the likely location of the endpoint of the vertical line on a valid trial, with the amount of unitary attention being largest at Location 1, next largest at Location 2, next largest at Location 3, and the least large at Location 4. This model would require that each stimulus be represented on four dimensions instead of two, where two of these dimensions are "invisible" on each trial. Although possible, a model of this sort has not been previously proposed in the literature. Like all theoretical issues, the best approach to the single versus multiple attention systems debate is to look at converging evidence from a variety of different sources. The present study represents a first step toward this goal.

At this point, it is worth mentioning briefly the relations between the present task and traditional spatial cuing designs (e.g., Eriksen & Hoffman, 1972; Posner, 1980). In the present task, the location of the spatial cue was fixed across trials, and the observer was instructed to visually fixate and focus perceptual attention on this location. On valid trials, the "target" (i.e., the horizontal line) was presented within the spatially cued location, and on invalid trials, the "target" was presented outside of the spatially cued location. On all trials, the observer was instructed to determine whether the target was *long* or *short*. There was a performance benefit on valid trials and a performance cost on invalid trials. In traditional spatial cuing tasks, the observer is instructed to fixate a centrally located fixation cue, and the spatial cue directs the observer's attention away from the fixation cue to one of several possible locations. On valid trials, the target is presented at the spatially cued location (although the eyes are to remain on the central fixation cue), and on invalid trials, the target is presented at one of the other possible locations. There is a performance benefit when the cue is valid and a performance cost when the cue is invalid.

Note that the tasks differ in at least three important respects. First, in the present task, the spatially cued location was visually fixated, whereas in most spatial cuing tasks, the spatially cued location differs from the fixated location. Second, in the present task, the spatially cued location was fixed across trials, whereas in most spatial cuing tasks, the location varies across trials. Third, in the present task, irrelevant information was provided in the spatially cued location on invalid trials, whereas in most spatial cuing tasks, no stimulus is presented in the spatially cued location on invalid trials. Despite these methodological differences, the basic findings are the same, thereby suggesting that a functional independence of perceptual and decisional attention is a robust phenomenon.

One variant of the traditional spatial cuing task is of particular relevance to the perceptual categorization literature. In this variant, the relation between spatial cuing and response expectancy is examined (e.g., Kingstone, 1992; Klein, 1994; Klein & Hansen, 1987, 1990). This literature suggests that the spatial cue is less effective when the target is less likely (i.e., has a lower base rate). For example, when a bright target is more likely than a dim target, the bright target shows the traditional cost–benefit effect of the spatial cue, whereas the dim target does not (e.g., Klein & Hansen, 1990). Base-rate effects are ubiquitous in perceptual categorization and have been found to affect the location and nature of the decision criterion (e.g., Maddox, in press). Future research should examine the influence of base-rate manipulations on performance when a spatial cuing manipulation is combined with a perceptual categorization task to determine whether the spatial cue and response expectancy interact in perceptual categorization in the same way as they do in traditional spatial cuing tasks.

In summary, in the present study, we examined the functional independence of perceptual and decisional attention during perceptual categorization by combining a perceptual categorization task with a spatial cuing manipulation. The empirical and model-based analyses strongly support the hypothesis that perceptual and decisional attention can function independently in perceptual categorization.

REFERENCES

Ashby, F. G. (1992a). Multidimensional models of categorization. In F. G. Ashby (Ed.), *Multidimensional models of perception and cognition* (pp. 449-484). Hillsdale, NJ: Erlbaum.

Ashby, F. G. (1992b). Multivariate probability distributions. In F. G. Ashby (Ed.), *Multidimensional models of perception and cognition* (pp. 1-34). Hillsdale, NJ: Erlbaum.

Ashby, F. G., Alfonso-Reese, L. A., Turken, A. U., & Waldron, E. M. (1998). A neuropsychological theory of multiple systems in category learning. *Psychological Review*, **105**, 442-481.

Ashby, F. G., Isen, A. M., & Turken, A. U. (1999). A neuropsychological theory of positive affect and its influence on cognition. *Psychological Review*, **106**, 529-550.

Ashby, F. G., & Lee, W. W. (1991). Predicting similarity and categorization from identification. *Journal of Experimental Psychology: General*, **120**, 150-172.

Ashby, F. G., & Lee, W. W. (1993). Perceptual variability as a fundamental axiom of perceptual science. In S. C. Masin (Ed.), *Foundations of perceptual theory* (pp. 369-399). Amsterdam: North-Holland.

Ashby, F. G., & Maddox, W. T. (1993). Relations between prototype, exemplar, and decision bound models of categorization. *Journal of Mathematical Psychology*, **37**, 372-400.

Ashby, F. G., & Townsend, J. T. (1986). Varieties of perceptual independence. *Psychological Review*, **93**, 154-179.

Braida, L. D., & Durlach, N. I. (1972). Intensity perception II: Resolution in one-interval paradigms. *Journal of the Acoustical Society of America*, **51**, 483-502.

Buchel, C., & Friston, K. J. (1997). Modulation of connectivity in visual pathways by attention: Cortical interactions evaluated with structural equation modeling and fMRI. *Cerebral Cortex*, **7**, 768-778.

Desimone, R., & Duncan, J. (1995). Neural mechanisms of selective visual attention. *Annual Review of Neuroscience*, **18**, 193-222.

Durlach, N. I., & Braida, L. D. (1969). Intensity perception I: Preliminary theory of intensity resolution. *Journal of the Acoustical Society of America*, **46**, 372-383.

Eriksen, C. W., & Hoffman, J. E. (1972). Temporal and spatial characteristics of selective encoding from visual displays. *Perception & Psychophysics*, **12**, 201-204.

Estes, W. K. (1994). *Classification and cognition*. Oxford: Oxford University Press.

Garner, W. R. (1974). *The processing of information and structure*. New York: Wiley.

Geisler, W. S. (1989). Sequential ideal-observer analysis of visual discriminations. *Psychological Review*, **96**, 267-341.

Goldman-Rakic, P. S. (1995). Toward a circuit model of working memory and the guidance of voluntary motor action. In J. C. Houk, J. L. Davis, & D. G. Beiser (Eds.), *Models of information processing in the basal ganglia* (pp. 131-148). Cambridge, MA: MIT Press, Bradford Books.

Goldstone, R. (1994). Influences of categorization on perceptual discrimination. *Journal of Experimental Psychology: General*, **123**, 178-200.

Green, D. M., & Swets, J. A. (1967). *Signal detection theory and psychophysics*. New York: Wiley.

Johnston, J. C., McCann, R. S., & Remington, R. W. (1995). Chronometric evidence for two types of attention. *Psychological Science*, **6**, 365-369.

Kingstone, A. (1992). Combining expectancies. *Quarterly Journal of Experimental Psychology*, **44A**, 69-104.

Klein, R. M. (1994). Perceptual-motor expectancies interact with covert visual orienting under conditions of endogenous but not exogenous control. *Canadian Journal of Experimental Psychology*, **48**, 167-181.

Klein, R. [M.], & Hansen, E. (1987). Spotlight failure in covert visual orienting. *Bulletin of the Psychonomic Society*, **25**, 447-450.

Klein, R. M., & Hansen, E. (1990). Chronometric analysis of apparent spotlight failure in endogenous visual orienting. *Journal of Experimental Psychology: Human Perception & Performance*, **16**, 790-801.

Knight, R. T. (1997). Distributed cortical network for visual attention. *Journal of Cognitive Neuroscience*, **9**, 75-91.

Kruschke, J. K. (1992). ALCOVE: An exemplar-based connectionist model of category learning. *Psychological Review*, **99**, 24-44.

LaBerge, D. (1997). Attention, awareness, and the triangular circuit. *Consciousness & Cognition*, **6**, 149-181.

Lamberts, K. (1995). Categorization under time pressure. *Journal of Experimental Psychology: General*, **124**, 161-180.

Lamberts, K. (1998). The time course of categorization. *Journal of Experimental Psychology: Learning, Memory, & Cognition*, **24**, 695-711.

Luce, R. D., & Green, D. M. (1978). Two tests of a neural attention hypothesis for auditory psychophysics. *Perception & Psychophysics*, **23**, 363-371.

Luce, R. D., & Nosofsky, R. M. (1984). Attention, stimulus range, and identification of loudness. In S. Kornblum & J. Requin (Eds.), *Preparatory states and processes* (pp. 3-25). Hillsdale, NJ: Erlbaum.

Macmillan, N. A., Goldberg, R. F., & Braida, L. D. (1988). Resolution for speech sounds: Basic sensitivity and context memory on vowel and consonant continua. *Journal of the Acoustical Society of America*, **84**, 1262-1280.

Maddox, W. T. (1992). Perceptual and decisional separability. In F. G. Ashby (Ed.), *Multidimensional models of perception and cognition* (pp. 147-180). Hillsdale, NJ: Erlbaum.

Maddox, W. T. (2002). Learning and attention in multidimensional identification and categorization: Separating low-level perceptual processes and high-level decisional processes. *Journal of Experimental Psychology: Learning, Memory, & Cognition*, **28**, 99-115.

Maddox, W. T. (in press). Toward a unified theory of decision criterion learning in perceptual categorization. *Journal of the Experimental Analysis of Behavior*.

Maddox, W. T., & Ashby, F. G. (1993). Comparing decision bound and exemplar models of categorization. *Perception & Psychophysics*, **53**, 49-70.

Maddox, W. T., & Ashby, F. G. (1998). Selective attention and the formation of linear decision boundaries: Comment on McKinley and Nosofsky (1996). *Journal of Experimental Psychology: Human Perception & Performance*, **24**, 301-321.

Maljkovic, V., & Nakayama, K. (1994). Priming of pop-out: I. The role of features. *Memory & Cognition*, **22**, 657-672.

Maljkovic, V., & Nakayama, K. (1996). Priming of pop-out: II. The role of position. *Perception & Psychophysics*, **58**, 977-991.

McCann, R. S., Folk, C. L., & Johnston, J. C. (1992). The role of attention in visual word processing. *Journal of Experimental Psychology: Human Perception & Performance*, **18**, 1015-1029.

Nosofsky, R. M. (1986). Attention, similarity, and the identification-categorization relationship. *Journal of Experimental Psychology: General*, **115**, 39-57.

Olshausen, B. A., Anderson, C. H., & Van Essen, D. C. (1993). A neurobiological model of visual attention and invariant pattern recognition based on dynamic routing of information. *Journal of Neuroscience*, **13**, 4700-4719.

Pashler, H. (1989). Dissociations and dependencies between speed and accuracy: Evidence for a two-component theory of divided attention in simple tasks. *Cognitive Psychology*, **21**, 469-514.

Pashler, H. (1991). Shifting visual attention and selecting motor responses: Distinct attentional mechanisms. *Journal of Experimental Psychology: Human Perception & Performance*, **17**, 1023-1040.

Pashler, H. (1993). Dual-task interference and elementary mental mechanisms. In D. E. Meyer & S. Kornblum (Eds.), *Attention and performance XIV* (pp. 245-263). Cambridge, MA: MIT Press.

Posner, M. I. (1980). Orienting of attention. *Quarterly Journal of Experimental Psychology*, **32**, 3-25.

Posner, M. I. (1993). Attention before and during the decade of the brain. In D. E. Meyer & S. Kornblum (Eds.), *Attention and performance XIV* (pp. 342-350). Cambridge, MA: MIT Press.

Posner, M. I., & Petersen, S. E. (1990). The attention system of the human brain. *Annual Review of Neuroscience*, **13**, 25-42.

Posner, M. I., Sandson, J., Dhawan, M., & Shulman, G. L. (1989). Is word recognition automatic? A cognitive-anatomical approach. *Journal of Cognitive Neuroscience*, **1**, 50-60.

Posner, M. I., Snyder, C. R. R., & Davidson, B. J. (1980). Attention and the detection of signals. *Journal of Experimental Psychology: General*, **109**, 160-174.

Rushworth, M. F., Nixon, P. D., Renowden, S., Wade, D. T., & Passingham, R. E. (1997). The left parietal cortex and motor attention. *Neuropsychologia*, **35**, 1261-1273.

Shepard, R. N. (1964). Attention and the metric structure of the stimulus space. *Journal of Mathematical Psychology*, **1**, 54-87.

Wickens, T. D. (1982). *Models for behavior: Stochastic processes in psychology*. San Francisco: Freeman.

NOTES

1. Although we structure our investigation in terms of *perceptual* and *decisional* attention, other frameworks have been used in the literature. For example, the term *spatial attention* is often used in the literature (e.g., Maljkovic & Nakayama, 1994, 1996). We deemed the perceptual/decisional attention distinction more appropriate for the present application for two reasons. First, most spatial cuing studies vary the attended location across trials and often manipulate other factors as well (Kingstone, 1992; Klein, 1994; Klein & Hansen, 1987, 1990), whereas our task manipulation was much simpler. We used a fixed spatial location while varying the stimulus information within the cued location. Thus it was the information that entered the perceptual system for processing that was manipulated. Second, the terms *perceptual* and *decisional* are more common in the categorization literature.

2. Before continuing, we must address one potential weakness of our experimental design. Recall that an irrelevant component judgment was required on some trials during Blocks 3–5, but not during Blocks 1–2. Specifically, during Blocks 3–5 one-fourth of the valid trials included ir-

relevant component judgments, whereas all of the invalid trials included irrelevant component judgments (see the Method section). This might bias the observer to place more importance on storing the irrelevant component length on invalid trials during Blocks 3–5 (when the irrelevant dimension was always cued) than during Blocks 1–2 (when the irrelevant dimension was never cued). If this hypothesis is correct, relevant dimension accuracy on invalid trials should be lower during Blocks 3–5 (when emphasis was placed on storing the irrelevant component) than during Blocks 1–2. We tested this hypothesis by computing relevant dimension accuracy on invalid trials separately for Blocks 1–2 and Blocks 3–5. Contrary to this hypothesis, accuracy was lower during Blocks 1–2 (76.3%) than during Blocks 3–5 (78.9%), and the difference was nonsignificant ($p > .10$). It is important to note, though, that even if this hypothesis was supported, it does not preclude us from distinguishing between yoked and functionally independent attention systems. In a yoked system, irrelevant judgments on valid trials and relevant judgments on invalid trials would be at chance, regardless of any decision bias. This follows because the decisional system has the information only in the cued location to operate on. When the information in the cued location is different from the information needed to generate a response, performance will be at chance regardless of any bias in the decision strategy. This pattern did not hold in the present study and thus provides evidence in support of the functional independence hypothesis.

3. Before we continue, two alternative explanations for the empirical results need to be ruled out. First, it is well established that resolution declines with eccentricity from the fovea (e.g., Geisler, 1989). Thus, one possibility is that performance is superior for the component in the spatial cue because that component has higher spatial resolution, regardless of whether separate attention systems exist. As a test of this alternative hypothesis, we performed two separate analyses. First, we compared relevant component accuracy on invalid trials when the irrelevant component was at its longest length with relevant component accuracy on invalid trials when the irrelevant component was at its shortest length. Invalid trials are those in which the irrelevant component is in the spatial cue. When the irrelevant component is at its shortest length, the relevant component will be at a smaller eccentricity than when the irrelevant component is at its longer length and thus should yield higher accuracy. Averaged across the 5 observers the accuracy rates were 80.5% and 74.3% for the long and short irrelevant components, respectively which is nonsignificant and in the opposite direction from that predicted by the *spatial resolution* hypothesis. Second, we compared irrelevant component accuracy on valid trials when the relevant component was at its longest length with irrelevant component accuracy on valid trials when the relevant component was at its shortest length. When the relevant component is at its shortest length, the irrelevant component will be at a smaller eccentricity than when the relevant component is at its longer length and thus should yield higher accuracy. Averaged across the 5 observers, the accuracy rates were 56.7% and 60.6% for the long and short relevant components, respectively, which is nonsignificant but in the predicted direction. Taken together, these analyses argue against any strong effect of eccentricity on the results. Second, it is possible that the circular spatial cue might serve as a reference frame for the component within the cued location. This would lead to higher accuracy for the component within the cued location relative to the component outside of the cued location. If this hypothesis is correct, it should be the case that performance would be better for long components within the spatial cue than for short components within the spatial cue, since the endpoints of long components would be closer to the reference frame. To test this, we compared accuracy for the relevant component on valid trials at the three shortest lengths with accuracy for the relevant component on valid trials at the three longest lengths. Averaged across observers, accuracy was 84.2% for the short and 86.6% for the long components. This difference was nonsignificant but is in the direction predicted by the *reference frame* hypothesis. We also compared accuracy for the irrelevant component on invalid trials at the three shortest lengths with accuracy for the irrelevant component on invalid trials at the three longest lengths. Averaged across observers, accuracy was 62.2% for the short and 56.0% for the long components. This difference was nonsignificant and was in direction opposite of that predicted by the reference frame hypothesis. Finally, because the reference frame hypothesis predicts that accuracy will be higher when the component is in the spatial cue, it predicts that accuracy will be higher for the relevant component on valid trials and for the irrelevant component on invalid trials than for the irrelevant component on valid trials and for the relevant component on invalid trials. This predicted ordering of accuracy was not observed in the data. Taken together, these analyses argue against the reference frame hypothesis.

4. It is important to note that this is a very restricted set of perceptual representation assumptions within the framework of decision bound theory. This version of decision bound theory assumes that the mean perceptual effects are located at the stimulus coordinates, that the perceptual noise across all 22 stimuli can be characterized by only two variance parameters, and that there is no perceptual correlation (i.e., perceptual independence is assumed; Ashby & Townsend, 1986). It is likely that at least some of these assumptions are violated with these stimuli. Even so, they are sufficient for the goals of the present study.

5. A version of the model that assumes a Gaussian similarity function was also applied. This version fit slightly better than the present version [average fit: EGCM(•,•) = 855.08; EGCM(P,•) = 846.27; EGCM(•,D) = 843.42; EGCM(P,D) = 842.88]. This version is not reported because the exponential similarity function is used in nearly all applications of exemplar theory. In addition, and perhaps more important, the parameter values from the Gaussian similarity function models are difficult to interpret. For example, in the Gaussian EGCM(•,D), the utility values are nearly all less than .5, suggesting more weight is being placed on the irrelevant dimension.

(Manuscript received January 10, 2001;
revision accepted for publication January 11, 2002.)