The prioritization of perceptual processing in categorization

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In three experiments, the effects of selective attention on perceptual processes in a complex multidimensional object categorization task were investigated. In each experiment, participants completed a perceptual-matching task to gain estimates of the perceptual salience of each stimulus dimension, then a categorization task using the same stimuli. In Experiments 1 and 2, the perceptual processing of stimulus dimensions was faster when dimensions were more diagnostic of category membership, regardless of their perceptual salience. Experiment 3 demonstrated that this prioritization of perceptual processing was evident even when stimuli were presented in unpredictable locations during categorization, indicating that the physical characteristics of the stimulus guide selective attention to diagnostic stimulus dimensions.

The influence of attention on perception has been the focus of much research in the last 30 years. Typically, the effects of visual attention have been examined using tasks in which attention is directed by a cue to a particular location and a judgment is required about a stimulus at this location. These paradigms have demonstrated that spatially cued attention enhances stimulus discrimination (Downing, 1988; Hawkins et al., 1990; Henderson, 1996; Lu & Doshier, 1998; Luck, Hillyard, Mouloua, & Hawkins, 1996; Posner, 1980), enhances spatial resolution (Carrasco, Williams, & Yeshurun, 2002; Yeshurun & Carrasco, 1998, 1999), increases contrast sensitivity (Carrasco, Ling, & Read, 2004), and even accelerates the rate at which visual information is processed (Carrasco & McElree, 2001). A number of physiological studies, including fMRI studies (Liu, Pestilli, & Carrasco, 2005), PET studies (Corbetta, Miezin, Dobmeyer, Shulman, & Petersen, 1990), ERP studies (Hillyard, Vogel, & Luck, 1998; Luck et al., 1994), and single-cell studies (Luck, Chelazzi, Hillyard, & Desimone, 1997; Moran & Desimone, 1985; see Treue, 2001, for a review), have also shown attention-related modulation of sensory processes. For example, attention increases spatial resolution by contracting a neuron's receptive field around the attended stimulus (e.g., Desimone & Duncan, 1995; Luck et al., 1997; Moran & Desimone, 1985; Reynolds & Desimone, 1999).

Despite these advances in understanding the influence of attention on perception, an unresolved issue concerns the extent to which attention influences perceptual processes in object categorization. In many models of categorization, the role of attention is located at the decision stage of categorization (Ashby & Gott, 1988; Estes, 1994; Nosofsky, 1986; Smith & Minda, 2000). For example, in Nosofsky's (1986) generalized context model (GCM), se-

lectively attending to an object dimension stretches the psychological distance between the object representation and stored representations that differ along that dimension, decreasing the similarity between them. Since attention is limited in capacity, selectively attending to one dimension contracts psychological distance along other, less attended object dimensions. By dynamically altering the similarity relationships between an object representation and stored representations, selective attention has a major influence on category decision. Nevertheless, it is recognized that under particular conditions, such as when perceptual confusability between stimuli is high, attention can also influence perceptual processes—for example, by decreasing the variability of perceptual representations of stimuli along the attended object dimension (Ennis, 1988; Nosofsky, 1988).

In order to examine the influence of attention on both decision and perception, it is necessary that a model of categorization should formally separate decision processes and perceptual processes. Two models that do this are decision bound theory (Ashby & Gott, 1988; Ashby & Maddox, 1994) and the extended generalized context model (EGCM; Lamberts, 1995, 1998, 2000). Maddox and colleagues have conducted a series of experiments using decision bound theory to examine the perceptual effects of attention in categorization (Maddox, 2001; Maddox & Bogdanov, 2000; Maddox & Dodd, 2003). These studies have shown that category structure—and hence, the type of decision required during categorization—appears to mediate any effects of attention on perception. In Maddox's experiments, category structure was manipulated so that attention needed to be directed either to both stimulus dimensions (integrated attention) or to a single stimulus dimension (decisional selective attention). Only

under conditions of decisional selective attention did attention influence perception by reducing the perceptual variance of the internal stimulus representation along the attended dimension. This perceptual effect of decisional selective attention was observed using both stimuli with separable dimensions (Maddox, 2001; Maddox & Bogdanov, 2000) and those with integral dimensions (Maddox & Dodd, 2003).

In categorization tasks requiring integration of information from three dimensions (all of which were relevant for successful categorization), Lamberts (1995, 1998) found that the diagnosticity of each dimension for category membership influenced decision processes (the weighting of each dimension in category decision), but not perceptual processes (the rate at which perceptual information was accumulated from each dimension). Thus, in accordance with the findings of Maddox and colleagues (Maddox, 2001; Maddox & Bogdanov, 2000; Maddox & Dodd, 2003), there appears to be minimal influence of selective attention on perceptual processes when categorization tasks are complex and require integration of information from multiple dimensions. A potential exception is the finding by Goldstone (1994) that, after participants learned to categorize objects, perceptual sensitivity in a subsequent matching task was enhanced along the dimension that was relevant for categorization. This was shown after categorization tasks involving decisional selective attention, but also in one task in which information from two dimensions was required to effectively categorize stimuli. Nevertheless, in all these cases, a relatively simple rule could have been used to learn the categories.

It has been suggested that category learning involves multiple systems that are localized in different brain regions (Ashby, Alfonso-Reese, Turken, & Waldron, 1998; Ashby, Ennis, & Spiering, 2007; Ashby, Noble, Filoteo, Waldron, & Ell, 2003; Filoteo et al., 2005; Maddox, Ashby, & Bohil, 2003; see Ashby & Maddox, 2005, and Maddox & Filoteo, 2005, for reviews). Ashby et al. (1998) proposed two distinct systems: an implicit procedural-based system that mediates category learning when it is necessary to integrate information from multiple dimensions and an explicit hypothesis-testing system that mediates rule-based category learning (but see Stanton & Nosofsky, 2007). Rule-based category learning requires that categories can be defined by a relatively simple rule that is easy to verbalize. Applying and testing such rules is thought to rely on working memory and attention (Filoteo, Lauritzen, & Maddox, in press). The explicit hypothesis-testing system is therefore thought to be mediated by the frontal cortices, whereas the implicit procedural system is mediated by the basal ganglia (see Ashby et al., 2007, for a recent review).

It is possible that use of the explicit hypothesis-testing system during category learning is necessary in order for attention to be effectively guided during subsequent categorization. In contrast, when categorization requires information integration from multiple relevant dimensions, it may be more difficult to allocate attention resources effectively. Indeed, the perceptual effects associated with visual attention, such as improved discrimination and

enhanced spatial resolution, have typically been demonstrated in tasks in which the whole object is cued (e.g., Luck et al., 1996). These effects may be less pronounced, or completely absent, in tasks such as categorization that require attentional resources to be split between multiple object features. Even so, feature-based attention can still modulate sensory processing (Martinez-Trujillo & Treue, 2004; Maunsell & Treue, 2006; Treue & Katzner, 2007; Treue & Martinez-Trujillo, 1999). Moreover, it is clear that people can learn complex category structures requiring information integration and are able to allocate attention effectively, demonstrated by efficient allocation of decisional weights (e.g., Lamberts, 1998) or placement of a decision bound (e.g., Ashby & Maddox, 1990).

Why, then, has no effect of attention on perceptual processes been observed in complex categorization tasks? This may reflect the existence of two forms of attention, decisional (or executive) attention and perceptual (visual) attention, that are served by different anatomical networks (Desimone & Duncan, 1995; Johnston, McCann, & Remington, 1995; LaBerge, 1997; Posner & Petersen, 1990). Indeed, Maddox, Ashby, and Waldron (2002) have shown that, in categorization, these two forms of attention can be oriented independently. In their task, a spatial cue was used to direct visual attention. Even when an irrelevant dimension was cued, the relevant dimension still received decisional attention. However, when visual attention is not controlled by a cue, there appears to be little reason why these two attentional systems should be directed independently. What value would there be in knowing the importance of different features for categorization (decisional attention) if visual attention could not be allocated to important sources of information?

Rehder and Hoffman (2005) demonstrated that, in a complex categorization task requiring information integration, decisional attention and visual attention tend to be closely coupled. In their experiment, they found that predictions derived from the GCM (Nosofsky, 1986) about the optimal distribution of selective attention to object features in a categorization task correlated well with the duration and number of fixations to these object features. Rehder and Hoffman's study therefore provides strong evidence that, even in a complex categorization task, visual attention resources can be split effectively among object dimensions.

In the present article, we reexamine whether selective attention can influence perceptual processes under conditions of voluntary attention allocation and in conditions in which categorization involves the integration of perceptual information from multiple dimensions. In particular, we focus on whether stimulus dimensions that are more diagnostic of categorization receive enhanced processing. Although Lamberts (1995, 1998) previously examined this issue, there are several reasons to believe that these studies may not have been sensitive enough to capture any influence of selective attention on perceptual processing.

Lamberts (1995, 1998) developed the EGCM in order to examine the influence of attention on perceptual processes in categorization. In the EGCM, it is assumed that, over the time of a perceptual-processing episode, sensory

information is sampled and accumulated to build a representation of the stimulus. As the stimulus representation is built up, its similarity to stored representations in memory (i.e., category exemplars) changes, altering the probability of producing different categorization responses. Crucially, it is assumed in the EGCM that sensory information from different stimulus dimensions can be accumulated at different rates.

Lamberts (1995, Experiment 3) examined the relationship between utility weights, which indicate the importance of stimulus dimension information in the decision process (this is formally identical to the operations of selective attention in the GCM), and the rate at which perceptual information from each feature was perceptually processed in a categorization task using stimuli that varied on three binary dimensions. Participants in the task first learned to categorize stimuli perfectly in a training stage (the assignment of the physical stimulus features to category dimensions was manipulated between participants), thus gaining an understanding of the relevance of each dimension (information from all dimensions had to be integrated to perfectly categorize stimuli). In the test phase, the participants were presented with transfer stimuli, and a response deadline procedure was used to manipulate the time available for perceptual processing. A strong effect of selective attention on the decision process (utility weights) was found, but no effect of selective attention on perceptual processes (processing rates). Utility weights were influenced by the abstract structure of the category, but processing rates were not. Rather, stimulus features were processed at rates determined by their physical salience (as rated by independent participants), regardless of the relevance of the dimension to which the physical feature was assigned. This finding was replicated by Lamberts (1998), with the modification that a signal-to-respond procedure was used, in which participants were not told on each trial how long they would have to respond (see Meyer, Irwin, Osman, & Kounios, 1988).

Several factors may have limited the sensitivity of Lamberts's (1995, 1998) experiments to effects of attention on perceptual processing. Lamberts's (1998) Experiment 2 improved on Lamberts's (1995) Experiment 3 by not providing pretrial information on whether responses were required early (after 100 msec) or late (respond when ready), preventing strategic influences on perceptual and decision processes. However, whereas performance after only 100 msec should have been near chance, due to the paucity of perceptual information, a high level of performance would be expected in the no-signal condition, in which perceptual information was comparatively rich. Nevertheless, for one of the assignment conditions, accuracy was quite low, even for stimuli whose category had been learned during training (accuracy was below 70% for four out of the six stimuli whose categories were learned in training). This suggests that the participants in this assignment condition had not learned the category structure adequately. If this were true, inefficient allocation of attention resources would result, potentially masking any effect of attention on perceptual processing.

Using only two signal intervals (100 msec or no signal) may have also not provided enough sensitivity to differences in perceptual processing rates between assignment conditions. Use of a response-signaling methodology typically includes many more signal intervals in order that information-processing rates may be reliably compared between experimental conditions (see Meyer et al., 1988). In addition, although perceptual salience was estimated by rating the salience of each stimulus dimension on a 7-point scale, this did not allow for a fine-grained analysis of exactly how much perceptual salience (and thus other factors, such as attention) influenced perceptual processing. Without a control task to provide estimates of perceptual-processing rates that reflect perceptual salience only, it is impossible to determine whether there has been any trade-off between processing rate parameters and utility weight parameters, potentially distorting modeling outcomes.

In order to address these concerns, the experiments reported in this article used an experimental design different from that of Lamberts (1995, 1998). Participants first complete a same/different perceptual-matching task and then complete a categorization task using the same stimuli. In the perceptual-matching task, two stimuli are presented sequentially (with both stimuli remaining visible), and participants are required to make a same/different judgment. The perceptual-matching task offers a much more rigorous method of measuring perceptual salience than do rating scales. Since a *difference* is equally likely on any of the dimensions, the time taken to respond *different* provides a good indication of the perceptual salience of the dimension on which the two stimuli differ. Previous applications of the perceptual-processing component of the EGCM to perceptual-matching tasks in order to estimate the rate at which stimulus dimensions were processed have been successful and have provided a good account of the time course of perceptual matching (e.g., Kent & Lamberts, 2006; Lamberts, Brockdorff, & Heit, 2002). The same technique was used here. This enabled comparison of perceptual-processing rates between the matching task and a categorization task, providing a more sensitive test of whether attention influenced perceptual processing in the categorization task.

In the categorization task, participants were trained to categorize eight stimuli varying on three binary dimensions. The category structure was designed so that there were clear differences in the diagnosticity of different stimulus dimensions, and the assignment of the physical features to category dimensions was such that there was no correlation between perceptual salience and dimension diagnosticity. To reduce any confusion created by the introduction of new stimuli at test, the participants were trained to categorize all stimuli in training. The criterion for training to be completed was stricter than that used by Lamberts (1995, 1998), ensuring that all the participants could categorize stimuli effectively. In the test phase of the categorization task, we used a larger number (four) of response signals than did Lamberts (1995, 1998) to increase the sensitivity of the design to differences in perceptual-processing rates between tasks.

EXPERIMENT 1

Method

Participants

Six students (2 of them female) from the University of Warwick took part in the experiment and were paid £4 (\$6.00) per hour. Two participants completed the matching task but were unable to learn to categorize the stimuli perfectly in the categorization task and so were excluded from the analyses. All the participants had normal or corrected-to-normal vision.

Apparatus and Stimuli

The stimuli were rendered computer-generated images of plants, which varied in appearance on three binary dimensions: flower (small or large), stem (thin or thick), and pot (ridged or not ridged). These three separable dimensions clearly corresponded to different object parts (Biederman, 1987; Hoffman & Richards, 1984; Marr & Nishihara, 1978). With these three binary dimensions, eight different stimuli were constructed, referred to by a binary code corresponding to the values of flower, stem, and pot, respectively. Stimuli 000 and 111 are shown in Figure 1. A Gateway GP6-400 Pentium II computer was used for stimulus presentation and response registration. The stimuli were presented on a 37-cm Gateway VX700 monitor, with a resolution of 800×600 pixels. Responses were given by means of two mounted buttons connected to the parallel port of the computer. The control software allowed response time (RT) registration with millisecond accuracy.

The participants viewed the screen from a distance of 130 cm. The stimuli were 14.4 cm tall (6.34°) and 6.2 cm wide (2.73°). In the matching task, the stimuli were presented ± 6.7 cm from the horizontal center of the screen and exactly at the vertical center of the screen. In the categorization task, the stimuli were presented at the center of the screen.

Design and Procedure

The participants were tested individually in a dimly lit room. The participants first completed a pairwise same/different matching task, in which a response-signaling procedure was used to limit RTs. Each trial in the matching task proceeded as follows. A small fixation cross was displayed centrally for 500 msec, followed by the presentation of the first stimulus on the left-hand side of the screen

(6.7 cm away from the horizontal center of the screen), where it remained for 2 sec (long enough to ensure complete processing). The second stimulus was then presented on the right side of the screen, again 6.7 cm away from the horizontal center of the screen. On each trial, the participants were instructed to respond immediately upon the onset of a response signal (a 500-Hz tone) that could sound 25, 75, 200, or 500 msec after the onset of the second stimulus. Thus, as in the categorization task, only the processing of a single stimulus could be interrupted. Both stimuli remained on the screen until a response was made. Immediately after the response, feedback was provided (a 2000-Hz tone indicated a correct response, and a 200-Hz tone indicated an incorrect response). A "Too Fast" warning sign was presented if a response was made prior to stimulus onset, and a "Too Slow" sign appeared if a response was not made within 350 msec after signal onset. The assignment of same/different to the left and right response buttons was counterbalanced across participants.

All possible different stimulus pairs (28 in total, ignoring presentation order) were presented at each signal interval. Therefore, a presented pair could differ in one feature, in two features, or in all features. Each stimulus pair was shown twice in each block of trials, counterbalancing the presentation order of the stimuli in the pair (thus producing 56 *different* trials for each signal interval). A total of 56 *same* pairs (7 *same* pairs for each stimulus) were also presented at each signal interval. A single block thus contained a total of 448 trials, the presentation order of which was randomized. Each participant completed six blocks, spread over several days. Within each block, the participants were allowed to take a break every 150 trials. The first block for all the participants was treated as a practice block and was excluded from the data analyses. The instructions emphasized the need to respond immediately after onset of the response signal, while maintaining the highest possible level of accuracy. The instructions also clarified that *same* responses should be given only to stimuli that were entirely identical and that any detected difference should lead to a *different* response.

In the categorization task, the eight stimuli were divided into two categories according to the category structure shown in Table 1. The categories were designed such that they could not be separated on the basis of any single dimension, ensuring that the participants could not perform the task by selectively processing a single stimulus feature. Dimensions 1 and 3 were equally diagnostic of category membership, each predicting 75% correct accuracy if categorization

Figure 1. Examples of stimuli in Experiments 1 and 2. (A) Stimulus 111. (B) Stimulus 000.

Table 1
Category Structure for Experiments 1, 2, and 3

Category	Stimulus	Dimension		
		1	2	3
A	1	0	0	0
	2	0	1	0
	3	1	1	0
	4	0	0	1
B	5	1	0	0
	6	0	1	1
	7	1	0	1
	8	1	1	1

Note—For Experiment 1, Dimensions 1, 2, and 3 corresponded to flower, stem, and pot, respectively. For Experiments 2 and 3, Dimensions 1, 2, and 3 corresponded to stem, flower, and pot, respectively.

were based on that dimension alone. Dimension 2 was not independently diagnostic of category membership.

There were two stages in the experiment: a training stage and a test stage. In the training stage, the participants learned to categorize the eight stimuli shown in Table 1. The stimuli were presented individually at the center of the screen. Responses were made via two mounted buttons labeled “Category A” and “Category B.” The assignment of the categories to the left and right buttons was counterbalanced across participants. After each response, correct–incorrect feedback was presented. Order of stimulus presentation was randomized, with the restriction that each stimulus occurred once in each block of 8 successive trials. Each participant had to complete a minimum of 10 blocks of 8 training trials. After these 80 trials, the training stage ended when the participant made no errors in 4 consecutive blocks of trials.

In the test stage, the participants were asked to categorize stimuli under time pressure. On each trial, a small fixation cross was displayed centrally for 500 msec, immediately followed by one of the training stimuli. The response-signaling procedure used was the same as that in the matching task, as were the signal intervals. Within a block of 32 trials, each stimulus was presented once at each signal interval, with the order in each block randomized. In total, 15 blocks of 32 trials were completed by each participant.

Results and Discussion

Matching

Overall, 16% of the responses were outside the 350-msec window from signal onset and were excluded from analysis. Generally, the percentage of responses outside the 350-msec response window diminished as signal interval increased. Proportions of correct responses and average RTs for each type of discrepancy (the feature or combination of features that differed between the pair of stimuli presented on a trial) at each signal interval are shown in Figure 2. As the signal interval increased, response accuracy generally increased, and the time to respond from the onset of the response signal decreased. The data from *different* trials (which contained two nonidentical stimuli) were of primary interest, because the detection rates of differences at different signal intervals provide information about feature-processing rates (see Lamberts et al., 2002). The data from the *same* trials (which contained two identical stimuli) can be used to provide an estimate of response bias but do not convey any information about feature salience. Response accuracy was generally worse when the stimuli differed on the pot feature, indicating that this was the least salient di-

mension. Accuracy was highest when the stimuli differed on the flower feature, indicating that this was the most salient dimension.

A repeated measures ANOVA on proportion correct for each type of discrepancy at each signal interval yielded a main effect of discrepancy [$F(7,21) = 28.57$, $MS_e = .010$, $p < .001$], a main effect of signal interval [$F(3,9) = 20.59$, $MS_e = .020$, $p < .001$], and a significant interaction between discrepancy and signal interval [$F(21,63) = 2.47$, $MS_e = .005$, $p = .003$]. To test whether the number of feature discrepancies had any effect on response accuracy, data were put into bins representing zero, one, two, or three feature discrepancies. A repeated measures ANOVA on proportion of correct responses for each of these bins at each signal interval showed that the main effect of number of discrepancies was significant [$F(3,9) = 20.48$, $MS_e = .006$, $p < .001$]. Performance improved as the number of discrepancies increased from one to three.

Categorization

At the training stage, the mean number of eight-trial blocks needed to reach criterion was 46 ($SD = 46.07$). In the test phase, 11% of the responses were outside the 350-msec response window and were excluded from analysis. Proportions of correct responses and average RTs for each stimulus at each signal interval are shown in Figure 3. As signal interval increased, proportion correct generally increased. Response accuracy at the 25-msec signal interval was above chance levels for Stimuli 1, 2, 7, and 8, close to chance levels for Stimuli 4 and 5, and below chance levels for Stimuli 3 and 6. As signal interval increased, accuracy generally increased for most stimuli, so that, at the longest signal interval, accuracy was well above chance for all the stimuli. For Stimuli 3 and 6, a crossover pattern of accuracy was observed in which errors were predominant at short signal intervals, with mainly correct responding at longer intervals. A repeated measures ANOVA on proportion correct for each type of stimulus at each signal interval yielded a main effect of stimulus [$F(7,21) = 7.07$, $MS_e = .049$, $p < .001$] and a main effect of signal interval [$F(3,9) = 18.04$, $MS_e = .027$, $p < .001$].

Modeling

The purpose of the formal modeling was to examine whether the perceptual processing of stimulus dimensions differed between the matching and categorization tasks. It was assumed in all model applications that perceptual processing of stimuli involves stochastic, parallel, and independent sampling of features (see Loftus, Busey, & Senders, 1993; Rumelhart, 1970; Townsend, Hu, & Ashby, 1981).

Matching. In the matching task, it was assumed that the presentation of the first stimulus for 2 sec was long enough to ensure full processing. Modeling, therefore, focused on the feature sampling of the second stimulus from the moment it was presented. We modeled data only from trials with different stimuli, although data from trials with identical stimuli informed the parameter estimation process (see below).

Figure 2. Observed proportions of correct responses, average response times (RTs; time from stimulus onset to response, in milliseconds), and predicted proportions of correct responses for the matching task in Experiments 1, 2, and 3. Numbers 1, 2, and 3 refer to trials on which stimuli differed on the flower, stem, and pot dimensions, respectively.

Figure 3. Observed proportions of correct responses, average response times (RTs; time from stimulus onset to response, in milliseconds), and predicted proportions of correct responses for the categorization task in Experiments 1 and 2.

The time t_{ij} available for processing at each signal interval i and for each condition j was given by

$$t_{ij} = RT_{ij} - t_{\text{res}}, \quad (1)$$

in which RT_{ij} is the observed RT from stimulus onset (not signal onset) in a given condition and t_{res} is a parameter that represents the time needed for decision making and response production (in all model applications, a separate t_{res} parameter was estimated for the categorization task and the matching task, since these tasks involved different decision processes).

The probability that stimulus feature x had been processed at or before time t_{ij} was assumed to be

$$p_x(t_{ij}) = [1 - \exp(-q_x \times t_{ij})]. \quad (2)$$

The parameter q_x is the inclusion rate of dimension x , which determines how quickly, on average, a dimension is processed.

The probability $p_{\text{det}}(t_{ij})$ that a difference between the stimuli had been detected in the allotted time t_{ij} was derived from the values of $p_x(t_{ij})$, on the assumption that stimulus dimensions were processed independently. For example, when the stimuli differed on dimensions x and y , the probability of detecting a difference was

$$p_{\text{det}}(t_{ij}) = p_x(t_{ij}) + p_y(t_{ij}) - p_x(t_{ij})p_y(t_{ij}). \quad (3)$$

The overall probability of a *different* response was derived from the difference detection probabilities using the single high threshold theory of discrimination (Macmillan & Creelman, 1990). Lamberts et al. (2002) previously applied this model to a similar perceptual-matching task. In the single high threshold model, the number of false alarms (the number of times a difference is reported without having been seen) at signal interval i (F_i) can be estimated from the proportion of *different* responses made at signal interval i on trials on which the stimuli were the same. Thus, F_i is essentially a measure of response bias. The total hit rate (i.e., the rate of responding *different* on trials with different stimuli) for condition j at signal interval i (H_{ij}) can then be predicted as

$$H_{ij} = p_{\text{det}}(t_{ij}) + [1 - p_{\text{det}}(t_{ij})] \times F_i, \quad (4)$$

in which $p_{\text{det}}(t_{ij})$ is the probability of detecting a difference at time t_{ij} .

We also fit the double high threshold theory of discrimination (Macmillan & Kaplan, 1985), but the single high threshold model provided the best compromise between a good fit and model parsimony.

Categorization. Categorization performance was modeled with the EGCM (Lamberts, 1995, 1998), which is an extension of the GCM (Nosofsky, 1986) and provides a detailed description of the perceptual-processing stage of categorization for objects with separable dimensions. In the EGCM, it is assumed that categorization is based on the similarity between a perceptual stimulus representation and category exemplars in memory. The similarity

between the stimulus and stored exemplars changes as perceptual information about the stimulus is processed. In the EGCM, similarity is defined by

$$s_{ab}(t_{ij}) = \exp \left\{ -c \left[\sum_{p=1}^P \text{inc}_p(t_{ij}) \times u_p |x_{ap} - x_{bp}| \right] \right\}, \quad (5)$$

in which P is the number of stimulus dimensions, and x_{ap} and x_{bp} are the values of stimulus a and stored exemplar b on dimension p . The parameter c is a scale parameter that reflects overall discriminability in the psychological space. The parameter u_p is the utility weight allocated to dimension p ($0 \leq u \leq 1$, $\sum u = 1$).

The parameter $\text{inc}_p(t_{ij})$ provides the link between similarity and perceptual processing. It takes a binary value that indicates whether dimension p has been processed (included) (1) or not (0) at time t . The probability of inclusion of each dimension is given by Equation 2. It is assumed that dimensions are processed independently. Thus, the probability of each possible inclusion pattern can be calculated. The probability of making a categorization choice for each inclusion pattern is calculated using the Luce (1963) choice rule. The probability that stimulus i is assigned to category J at time t is given by

$$P(R_J | \text{Stim}_i, t) = \frac{b_J \sum_{j \in C_J} s_{ij}(t)}{\sum_{K=1}^m \left[b_K \sum_{k \in C_K} s_{ik}(t) \right]}, \quad (6)$$

in which s_{ij} is the similarity between stimulus i and stored exemplar j , m is the number of categories, b_J represents the bias for making response J ($\sum b = 1$), and the index $j \in C_J$ refers to all stored exemplars that belong to category J . The predicted probability of making a category choice for a particular stimulus at a particular time is the sum of the products of the probability of each inclusion pattern and the probability of making a category response for that inclusion pattern.

Model Application

Data from the matching and categorization tasks were fit simultaneously. The most general model had 12 free parameters: six processing rates (one q for each feature in each task), two residual time parameters (one t_{res} for each task), two utility weights (the third constrained by the other two), a bias value (b), and a generalization value (c). This general model yielded an overall log likelihood value of -186.37 and accounted for 88.4% and 93.91% of the variance in response proportions for the matching and categorization tasks, respectively. To examine whether the processing rates of stimulus features differed between the matching and categorization tasks, a model was applied in which the processing rate of each particular feature was the same in the matching task and the categorization task (a 9-parameter model). This restricted model fit the data reliably worse than the most general model [$\chi^2(3) = 18.21$, $p < .001$], indicating that the same stimulus features were processed at different rates in matching and categorization.

Table 2
Estimated Feature-Processing Rates for the 12-Parameter Model
Applied to Averaged and Individual Participant Data From
the Matching and Categorization Tasks in Experiments 1 and 2

Participant		Flower	Stem	Pot	Significance
Experiment 1					
Average data	Matching	.0070	.0045	.0030	**
	Categorization	.0181	.0026	.0075	
A.B.	Matching	.0089	.0046	.0029	
	Categorization	.0184	.0044	.0024	
D.A.	Matching	.0106	.0056	.0033	**
	Categorization	.0419	.0025	.0012	
M.J.	Matching	.0060	.0041	.0036	**
	Categorization	.3674	.0069	.0474	
P.M.	Matching	.0060	.0047	.0028	**
	Categorization	.0148	.0025	.0049	
Experiment 2					
Average data	Matching	.0079	.0045	.0014	**
	Categorization	.0029	.0087	.0082	
A.W.	Matching	.0035	.0013	.0014	
	Categorization	.0022	.0039	.0016	
I.Y.	Matching	.0086	.0064	.0002	*
	Categorization	.0580	.0074	.0031	
J.J.	Matching	.0080	.0062	.0016	*
	Categorization	.0040	.0120	.0030	
J.K.G.	Matching	.0201	.0075	.0041	**
	Categorization	.0014	.0008	.0368	
R.S.	Matching	.0089	.0054	.0012	**
	Categorization	.0031	.0390	.0069	

Note—Results of a likelihood ratio test between this 12-parameter model and a 9-parameter model, in which processing rates were assumed to be the same between tasks, are given in the final column (* $p < .1$, ** $p < .05$).

Table 2 shows the estimated processing rates in the matching and categorization tasks. The rank order of feature-processing rates in the matching task was flower > stem > pot, where the flower feature was processed most rapidly and the pot feature most slowly. In comparison, the rank order of feature-processing rates was flower > pot > stem in the categorization task. Thus, the ordinal relationship of the stem and pot processing rates differed between tasks. The direction of this change is predicted by the diagnosticity of the stimulus features in the categorization task (see Table 1). The stem dimension was least diagnostic of category membership, predicting 50% accuracy if the responses were based on this dimension alone, whereas the flower and pot dimensions were much more diagnostic, predicting 75% accuracy if the responses were based on either dimension.

In contrast with the findings of Lamberts (1995, 1998), feature diagnosticity appeared to have a large influence on feature processing, with the stimulus features that were more diagnostic being processed most rapidly. In addition, both the highly diagnostic features were processed at faster rates in categorization than in matching, whereas the least diagnostic feature was processed at a slower rate in categorization than in matching. This suggests that feature diagnosticity influenced the allocation of attentional resources in the categorization task, such that the processing of highly diagnostic dimensions was enhanced at the expense of processing the least diagnostic dimen-

sion. Although perceptual salience was not the main determinant of processing rate, it did appear to play a minor role, since the flower feature was processed more rapidly than the equally diagnostic but less perceptually salient pot feature.

In order to demonstrate that these model outcomes were not artifacts of fitting data averaged across participants (see Maddox, 1999), the same modeling procedure was applied to individual participant data. The estimated processing rates for each participant are shown in Table 2. The rank order of feature processing was flower > stem > pot in the matching task for all the participants. Relative to the feature-processing rates in the matching task, in the categorization task, all 4 participants showed faster processing of the highly diagnostic flower feature, 2 participants showed faster processing of the highly diagnostic pot feature, and 3 participants showed slower processing of the least diagnostic stem feature. The difference in feature-processing rates between tasks was such that the rank order of feature-processing rates differed between matching and categorization for 2 participants. The modeling of individual participant data therefore supported the conclusions drawn from modeling data averaged across participants: Stimulus features that were more diagnostic of category membership were processed more rapidly in categorization, whereas the least diagnostic dimension was processed more slowly, relative to the matching task.

Since modeling the average data indicated that feature-processing rates differed between matching and categorization tasks, the 12-parameter model that best fit the data essentially comprised a 4-parameter model that was fit to the matching data and an 8-parameter model that was fit to the categorization data. The predicted response proportions of the 4-parameter model applied to the average data from the matching task are shown against observed response proportions in Figure 2. Overall, the 4-parameter model provided a very good fit of the matching data, capturing well the manner in which accuracy increased as signal interval increased for each type of discrepancy and correctly predicting that response accuracy was highest when there was a discrepancy in the flower dimension and lowest when there was a discrepancy in the pot dimension.

Although modeling individual and average data revealed that processing rates differed systematically between matching and categorization tasks, this type of modeling analysis differed considerably from that used by Lamberts (1995, 1998). In Lamberts (1995, 1998), the assignment of physical stimulus features to abstract dimensions was manipulated between participants, and the utility weights and processing rates were compared between assignment groups. It is possible that the contrasting findings between these studies and the present study are due to the different modeling methodologies used. In order to replicate the between-participants modeling analysis used by Lamberts (1995, 1998), Experiment 2 was identical to Experiment 1 except that the assignment of stimulus features to abstract category dimensions (the diagnosticity of each feature) was altered (see Table 1). This enabled models to be fit to categorization data from Experiments 1 and 2 simultaneously. We therefore postpone discussing the fit of models to categorization data from Experiment 1 until the Model Application section of Experiment 2. If the processing of diagnostic features is enhanced by allocating greater attentional resources to them, systematic differences in feature-processing rates should be observed between the categorization tasks and, as in Experiment 1, systematic differences in feature-processing rates should also be observed between categorization and matching tasks.

EXPERIMENT 2

Method

Participants

Six students (3 of them female) from the University of Warwick took part in the experiment and were paid £4 (\$6.00) per hour. One participant completed the matching task but was unable to learn to categorize stimuli perfectly in the categorization task and so was excluded from the analyses. All the participants had normal or corrected-to-normal vision.

Apparatus and Stimuli

The apparatus and stimuli were the same as those used in Experiment 1.

Design and Procedure

The design and procedure were identical to those in Experiment 1, except for the assignment of the stimulus features to the category dimensions (see Table 1).

Results and Discussion

Matching

Overall, 16% of the responses were outside the 350-msec response window. As signal interval increased, the amount of responses outside the response window tended to decrease. Figure 2 shows the proportions of correct responses against average RTs (from stimulus onset) for each type of discrepancy at each signal interval. Performance levels at each signal interval and each kind of discrepancy were very similar to those observed in Experiment 1. The exception was that accuracy for noticing a single discrepancy on the pot dimension was worse in Experiment 2. Overall, though, the results of the matching task in Experiment 2 replicated those from Experiment 1 and indicated that the flower was the most salient stimulus feature and the pot the least salient stimulus feature.

A repeated measures ANOVA on proportion correct for each type of discrepancy at each signal interval yielded a main effect of discrepancy [$F(7,28) = 29.49$, $MS_e = .023$, $p < .001$], a main effect of signal interval [$F(3,12) = 28.14$, $MS_e = .037$, $p < .001$], and a significant interaction between discrepancy and signal interval [$F(21,84) = 1.83$, $MS_e = .006$, $p = .028$]. As in Experiment 1, an ANOVA on proportion of correct responses for data placed in bins representing zero, one, two, or three feature discrepancies showed that the main effect of number of discrepancies was significant [$F(3,12) = 66.57$, $MS_e = .005$, $p < .001$]. Performance improved as the number of discrepancies increased from one to three.

Categorization

At the training stage, the mean number of eight-trial blocks needed to reach criterion was 24 ($SD = 2.56$). In the test stage, 21% of the responses were outside the 350-msec response window and so were excluded from analysis. Proportion of correct responding and average RT for each stimulus at each signal interval are shown in Figure 3. Response accuracy at the 25-msec signal interval was above chance levels for Stimuli 1 and 8, close to chance levels for Stimuli 2, 3, 4, and 7, and slightly below chance for Stimuli 5 and 6. Generally, accuracy increased as signal interval increased, such that, at the longest signal interval, accuracy was well above chance for all the stimuli. A slight crossover pattern of response accuracy was observed for Stimuli 5 and 6. A repeated measures ANOVA on proportion correct for each type of stimulus at each signal interval yielded a main effect of signal interval only [$F(3,12) = 26.51$, $MS_e = .024$, $p < .001$].

Model Application

The model-based analysis described in Experiment 1 was repeated here. The most general model (12 param-

ters), fit to data from the matching and categorization tasks simultaneously, yielded an overall log likelihood value of -172.83 . The log likelihood values were -88.63 and -94.19 for the matching and categorization tasks, respectively, and the model accounted for 96.83% and 93.61% of the variance in response proportions, respectively. A restricted 9-parameter model in which feature-processing rates were assumed to be the same between tasks fit the data reliably worse than did the 12-parameter model [$\chi^2(3) = 39.23, p < .001$], indicating that the same stimulus features were processed at different rates in matching and categorization. Table 2 shows the estimated parameter values for the processing rates of the 12-parameter model in the matching and categorization tasks. As in Experiment 1, the rank order of feature-processing rates in the matching task was flower > stem > pot. However, the rank order of feature-processing rates in the categorization task was stem > pot > flower. As in Experiment 1, the diagnostic stimulus features (in this case, the stem and pot features) were processed most rapidly, whereas the least diagnostic flower feature was processed most slowly. Again, perceptual salience did appear to play a minor role in determining processing rates in the categorization task, with the most perceptually salient of the two equally diagnostic stimulus features (the stem and pot) being processed most rapidly. Nevertheless, perceptual salience did not dominate perceptual processing, as it did in the Lamberts (1995, 1998) experiments.

In order to check that these modeling results were not artifacts of fitting data averaged across participants, the same modeling analysis was completed on individual participant data and is shown in Table 2. For all the participants except 1 (who showed a slightly faster rate of processing for the pot feature, relative to the stem feature), the rank order of feature processing was flower > stem > pot in the matching task. Relative to the feature-processing rates in the matching task, in the categorization task, 4 participants showed faster processing of the highly diagnostic stem feature, 5 participants showed faster processing of the highly diagnostic pot feature, and 4 participants showed slower processing of the least diagnostic flower feature. These differences meant that the rank order of feature processing differed between matching and categorization for 4 participants. Modeling individual participant data therefore supported the conclusions drawn from modeling data averaged across participants: Feature diagnosticity influenced feature processing in categorization, such that features were processed at different rates in both tasks.

The fit of the 4-parameter model applied to the matching data averaged across participants (this model was nested in the most general 12-parameter model outlined above) is shown against observed proportions of correct responses in Figure 2. The model accurately predicted the different levels of performance for each type of discrepancy and captured the manner in which accuracy increased as signal interval increased for each type of discrepancy.

A central motivation for manipulating the assignment of physical stimulus features to abstract dimensions between Experiments 1 and 2 was to enable use of a between-

subjects modeling method similar to that used by Lamberts (1995, 1998). A selection of models was therefore fit to data from both categorization tasks simultaneously. The most general model had 13 parameters, three processing rates for each categorization task (one q for each feature), two utility weights for each categorization task (the third constrained by the other two), a residual time parameter, a bias value (b), and a generalization value (c). The log likelihood yielded by this model is shown in Figure 4, alongside the log likelihoods yielded by other nested models. As is shown in Figure 4, restricting this model by assuming that stimulus features were processed at the same rate in each task significantly reduced model fit. In comparison, assuming that utility weights were the same in each categorization task did not significantly reduce model fit; neither did assuming that utility weights were equal (.33) across all dimensions. Thus, the difference in performance between the categorization tasks was due to differences in feature-processing rates, rather than to differences in the utility weights assigned to the category dimensions.

To examine whether different features were processed at different rates within each categorization task, a model was fit to the data in which a single processing rate was estimated for all features within each categorization task. This model fit the data significantly worse, indicating that stimulus features within each categorization task were processed at different rates. Finally, to examine the relationship between processing rates in the categorization tasks and those in the matching task, a model was applied in which the processing rates in the categorization tasks

Figure 4. Nested comparisons for models fit to the categorization data (averaged across participants) in Experiments 1 and 2. Model fits are given by log likelihood values (log L), and fits between models were compared using likelihood ratio tests. The model that provided the best balance between model fit and model parsimony is shown in bold.

were constrained to be in the same rank order as that in matching (flower > stem > pot). Constraining the processing rates in this manner significantly reduced model fit, indicating that the rank order of processing rates (as well as absolute values) differed between the matching and categorization tasks.

Overall, the model that provided the best balance between fit of the categorization data and parsimony had nine parameters: six processing rates (one q for each feature in each categorization task), a residual time parameter (t_{res}), a bias value (b), and a generalization value (c) (sharing the parameters c , b , and t_{res} between categorization tasks did not significantly deteriorate model fit). This yielded a log likelihood value of -174.99 and accounted for 93.7% and 93% of the variance in proportions of correct responses in the categorization task in Experiments 1 and 2, respectively. The predicted response proportions from this nine-parameter model are shown alongside observed proportions of correct responses in Figure 3. The model provided a good account of the categorization data. It successfully predicted the differences in response accuracy for different stimuli and provided a good account of the way in which accuracy for each stimulus generally increased as signal interval increased. In particular, it captured the crossover pattern of response accuracy observed for Stimuli 3 and 6 in Experiment 1, whereby these stimuli were categorized incorrectly at the shortest signal interval but correctly at the longest signal interval. Lamberts and Freeman (1999) previously demonstrated that these crossover patterns provide considerable problems for other models of categorization, such as the exemplar-based random walk model (Nosofsky & Palmeri, 1997). However, the model failed to capture the crossover patterns of response accuracy observed for Stimuli 5 and 6 in Experiment 2.

In Experiment 1, model predictions were worst for Stimuli 2 and 8, for which the model consistently underpredicted response accuracy at each signal interval, and for Stimulus 3, where the model failed to capture the sharp increase in response accuracy at the 75-msec signal interval and the subsequent decrease in response accuracy at the 200-msec signal interval. In Experiment 2, the model predictions were worst for Stimuli 2 and 5, for which the model tended to overpredict response accuracy at each signal interval.

The parameter values for the nine-parameter model applied to data from the categorization task in Experiments 1 and 2 are shown in Table 3. The parameter values for each of the four-parameter models applied to data from the matching task in Experiment 1 and the matching task in Experiment 2 are also shown for ease of comparison. In the two categorization tasks, the rank order of feature processing differed considerably. These differences were predicted by feature diagnosticity, with highly diagnostic object features being processed more quickly. Consistent with the modeling analysis completed on matching and categorization data from each task, the between-participants modeling of the categorization data indicated that the highly diagnostic stimulus features were processed at faster rates in categorization than in matching, whereas the least diagnostic dimension was processed at a slower rate than in matching.

EXPERIMENT 3

Although showing that more diagnostic stimulus features are selectively attended and processed during categorization, Experiments 1 and 2 provide limited insight into the mechanisms through which feature diagnosticity exerts its influence on perceptual processing. In both experiments, the allocation of attentional resources could have occurred prior to or during stimulus presentation. On each trial, stimuli were presented in exactly the same place relative to the cue, enabling attention to be directed to the locations at which diagnostic features were to appear prior to stimulus onset. Kristjánsson, Mackeben, and Nakayama (2001) have shown that the spatial relationship between the cue and target locations can influence how attention is deployed in a search task. When a particular area in the display is cued, the location at which a target is presented within this cued area influences performance such that performance is enhanced when the target always appears at a specific location in the cued area. It is therefore possible that the consistent spatial mapping between the cue location and stimulus location in the categorization tasks in Experiments 1 and 2 may have led to attentional resources being directed to the locations of diagnostic stimulus dimensions before stimulus presentation, enhancing their processing.

Table 3
Parameter Values for the Best-Fitting Four-Parameter Models Applied to the Matching Data From Experiments 1 and 2 and for the Nine-Parameter Model Applied to the Categorization Data From Experiments 1 and 2

Parameter	Matching		Parameter	Categorization
	Experiment 1	Experiment 2		Experiments 1 and 2
q (flower)	.0070	.0079	q (flower), Experiment 1	.0169
q (stem)	.0045	.0045	q (stem), Experiment 1	.0025
q (pot)	.0030	.0014	q (pot), Experiment 1	.0041
t_{res}	196.57	172.98	q (flower), Experiment 2	.0026
			q (stem), Experiment 2	.0051
			q (pot), Experiment 2	.0036
			c	28.97
			b	.51
			t_{res}	245.33

Alternatively, the mechanism directing attention toward the diagnostic features in the categorization task could have operated after stimulus presentation. There is a wealth of evidence demonstrating that attention can be efficiently directed to objects with features that are task relevant (Folk, Remington, & Johnston, 1992). Presumably, at the training stage of the categorization tasks, participants learn how diagnostic each feature is of category membership. Knowledge of the physical characteristics associated with each dimension (color, shape, etc.) can then be used to guide attention toward the diagnostic features upon stimulus presentation, enhancing their processing.

The purpose of Experiment 3 was to determine the temporal locus of attention allocation in the categorization task. Specifically, the experiment was designed to determine whether allocation of attention resources to diagnostic features occurs prior to or during stimulus presentation. The design was similar to that in Experiments 1 and 2, except that, in the test phase of the categorization task, the location of the stimulus on the display was unpredictable. Any influence of dimension diagnosticity on perceptual processing would, therefore, be caused by allocation of attention resources toward diagnostic stimulus dimensions after stimulus onset.

Method

Participants

Four (female) students from the University of Warwick took part in the experiment and were paid £5 (\$7.50) per session. All the participants had normal or corrected-to-normal vision.

Stimuli, Apparatus, Design, and Procedure

The matching task and categorization training stage were exactly the same as those in Experiment 2 (including the assignment of stimulus features to category dimensions). The test phase was similar to that in Experiment 1, except that the stimuli could be presented at any of four locations on the screen. At each location, the center of a presented stimulus was ± 7.7 cm from the cue (which was in the center of the screen) on the horizontal axis and ± 3.3 cm above or below the cue on the vertical axis. Within a block, each stimulus was presented at each signal interval at each location. Twenty blocks of 128 trials were completed by each participant. One block took approximately 10 min to complete. The participants took part in four test sessions. At the beginning of each session, the participants had to complete the training stage to make sure that they still remembered the category structure.

Results and Discussion

Matching

Overall, 20% of the responses were outside the 350-msec response window and were excluded from further analysis. Figure 2 shows the proportion of correct responding and average RTs for each type of discrepancy at each signal interval. As signal interval increased, response accuracy increased. The qualitative pattern of responses matched those in Experiments 1 and 2, with more discrepancies noticed for the flower feature and the least discrepancies noticed for the pot feature. A repeated measures ANOVA on the proportion of correct responses, with signal interval and discrepancy as independent variables, yielded a main effect of signal interval [$F(3,9) = 12.33$, $MS_e = .02$, $p = .002$], a main effect of discrepancy [$F(7,21) = 15.60$,

$MS_e = .036$, $p < .001$], and a significant interaction between signal interval and discrepancy [$F(21,63) = 2.67$, $MS_e = .008$, $p < .001$]. As in Experiment 1, an ANOVA on proportion of correct responses for data placed in bins representing zero, one, two, or three feature discrepancies showed that the main effect of number of discrepancies was significant [$F(3,9) = 13.70$, $MS_e = .015$, $p = .021$]. Performance improved as the number of discrepancies increased from one to three.

Categorization

At the training stage for the first session, the mean number of eight-trial blocks needed to reach criterion was 35 ($SD = 18.53$). In further training sessions, the mean number of blocks needed to reach criterion was 11.62 ($SD = 3.55$). In the test phase, 31% of the responses were outside the response window and were excluded from further analysis. Figure 5 shows the proportion of correct responding and average RTs for each stimulus at each location and each signal interval. Overall, as signal interval increased, response accuracy increased. Response accuracy was generally highest for Stimulus 1 and lowest for Stimulus 5. A repeated measures ANOVA on proportion of correct responses for each stimulus at each presentation location and at each signal interval yielded a significant main effect of signal interval [$F(3,9) = 132.78$, $MS_e = .44$, $p < .001$]. All other main effects and interactions, including any effects of location, were not significant.

Modeling and Discussion

In all model applications, the model was fit to response proportions at each presentation location. However, since there were no significant differences between response proportions at the different presentation locations, it was assumed that the values of model parameters were the same for each location. Modeling analysis proceeded as in Experiment 1. The most general 12-parameter model was fit to the data, yielding a log likelihood value of -459.02 and accounting for 93.6% of the variance in proportions of correct responses in the matching task and 91.6% of the variance in proportions of correct responses in the categorization task.

To examine whether features were processed at similar rates in matching and categorization, a restricted 9-parameter model in which only three processing rates were estimated (the processing rate of each feature was the same in both tasks) was fit to the data. This restricted model fit the data reliably worse than the most general 12-parameter model [$\chi^2(3) = 166.90$, $p < .001$], indicating that features were processed at different rates in the two tasks. To examine whether the rank order of feature-processing rates differed between the tasks (and not simply whether the absolute values of processing rates were the same in each task), a model was fit to the data in which the rank order of processing rates in the categorization task was the same as that in the matching task (flower > stem > pot). Although having the same number of parameters as the most general model, this constrained model fit the data significantly worse [$\chi^2(1) = 5.92$, $p < .025$], assuming that the constraint imposed on processing rates

Figure 5. Observed proportions of correct responses (O), average response times (RTs; time from stimulus onset to response, in milliseconds), and predicted proportions of correct responses (P) for the categorization task in Experiment 3 for locations of top left, bottom left, top right, and bottom right (L1–L4, respectively).

Table 4
Best-Fitting Parameter Values for the 10-Parameter Model
Applied to the Data From Experiment 3

Parameter	Value	
	Matching	Categorization
<i>q</i> (flower)	.0110	.0040
<i>q</i> (stem)	.0049	.0061
<i>q</i> (pot)	.0020	.0072
<i>t</i> _{res}	190.31	271.57
<i>c</i>		15.58
<i>b</i>		.44

was equal to a difference of 1 parameter]. Further comparisons showed that restricting the most general model further by assuming equal utility weights did not significantly deteriorate model fit [$\chi^2(2) = 5.67, p > .05$].

The fit of the 10-parameter model (the 12-parameter model minus the two utility weights) to the matching and categorization data is shown in Figures 2 and 5, respectively. Overall, the model provided a good fit of the matching data. It successfully predicted the differences in response accuracy observed for different discrepancies and captured the manner in which response accuracy for each discrepancy increased as signal interval increased. The model fit was worst when the stimuli differed on the pot feature. For this discrepancy, the model overpredicted response accuracy at the shorter signal intervals and underpredicted response accuracy at the longest signal interval. The 10-parameter model also fit the categorization data well, accounting for 91.6% of the variance in proportions of correct responses. The model successfully captured the increase in response accuracy with increasing signal interval for each stimulus. However, the model failed to capture the crossover pattern of accuracy for Stimulus 5. Furthermore, it tended to overpredict response accuracy for Stimuli 2 and 5 and underpredict response accuracy for Stimuli 1 and 6.

The best-fitting parameter values of the 10-parameter model are shown in Table 4. As in Experiments 1 and 2, the feature-processing rates for the matching task were in the rank order flower > stem > pot, with the flower being processed most rapidly. However, in the categorization task, the feature-processing rates were in the rank order

pot > stem > flower. Thus, despite manipulating the presentation location, the two highly diagnostic features (the pot and stem) were processed at faster rates than the more perceptually salient flower feature.

Table 5 shows the processing rate parameters for the most general, 12-parameter model, fit to individual participant data. In the matching task, the rank order of feature processing was flower > stem > pot for all the participants. However, relative to the feature-processing rates in the matching task, in the categorization task, all 4 participants showed slower processing of the highly salient but least diagnostic flower feature, 3 showed faster processing of the highly diagnostic stem feature, and 3 showed faster processing of the highly diagnostic pot feature. These differences in processing rates between tasks meant that, for all 4 participants, the rank order of feature processing differed between categorization and matching.

Individual participant modeling, therefore, supported the conclusions drawn from modeling data averaged across participants. Feature processing in categorization is influenced by feature diagnosticity such that features that are more diagnostic of category membership tend to be processed more rapidly. Furthermore, although highly diagnostic stimulus features appear to receive enhanced processing in categorization, relative to matching, processing of the least diagnostic feature is slowed in categorization, relative to matching. This is consistent with the results of Experiments 1 and 2 and suggests that allocating more attentional resources to the highly diagnostic stimulus features enhances their processing at the expense of the processing of the least diagnostic stimulus feature. Given that the stimuli were randomly presented at one of four locations, the observed prioritization of feature processing in the categorization task in Experiment 3 suggests that the physical characteristics of the diagnostic stimulus features guided attention to highly diagnostic stimulus features during categorization, enabling selective processing of these features.

GENERAL DISCUSSION

In models of perceptual categorization, decision processes are assumed to be affected by selective attention

Table 5
Estimated Feature-Processing Rates for the 12-Parameter Model
Applied to Individual Participant Data From the Matching and
Categorization Tasks in Experiment 3

Participant		Flower	Stem	Pot	Significance
A.A.	Matching	.0088	.0054	.0043	*
	Categorization	.0073	.0096	.0065	
M.H.	Matching	.0100	.0062	.0022	**
	Categorization	.0035	.0133	.0019	
S.Y.	Matching	.0139	.0036	.0031	**
	Categorization	.0076	.0131	.0095	
T.L.	Matching	.0130	.0069	.0005	**
	Categorization	.0030	.0019	.5794	

Note—Results of a likelihood ratio test between this 12-parameter model and a 9-parameter model, in which processing rates were assumed to be the same between tasks, are given in the final column (* $p < .1$, ** $p < .05$).

(e.g., Nosofsky, 1986). Whereas it has been recognized that selective attention may also influence perceptual processes, this has been observed only under particular conditions—that is, those in which a single dimension is relevant for categorization (Maddox, 2001; Maddox & Bogdanov, 2000; Maddox & Dodd, 2003). It is perhaps surprising that perceptual effects of selective attention have been reported only under these limited conditions, given the wealth of evidence showing that visual attention modulates sensory processing by increasing discriminability and accelerating processing rates (Carrasco & McElree, 2001; Downing, 1988; Luck et al., 1994; Treue, 2001). The experiments presented here reexamined whether selective attention can influence perceptual processing in a complex categorization task in which successful categorization is dependent on integration of information from multiple dimensions. In particular, we examined whether selectively attending to a stimulus feature enhances the rate at which the feature is processed. Although previous studies had failed to yield evidence of any such enhancement (Lamberts, 1995, 1998), we used a new methodology, which offered a more sensitive measurement of possible effects of attention on feature-processing rates.

In three experiments, participants completed a perceptual-matching task and a categorization task involving the same stimuli. The matching task was used to derive feature-processing rates in a context in which all the features were equally relevant (implying that these rates reflected perceptual salience). In the categorization tasks, the category structure was manipulated so that the diagnosticity of the stimulus features was dissociated from their perceptual salience (as measured by the matching task). Participants were first trained to categorize stimuli and, subsequently, made speeded category judgments to individual stimuli under differing amounts of time pressure.

Experiments 1 and 2 were identical except for the assignment of physical stimulus features to the underlying, abstract category structure. In both experiments, feature-processing rates in categorization differed markedly from those in the matching task (which was the same in both experiments). In the categorization tasks, processing rates were influenced by diagnosticity, with the most diagnostic features processed most rapidly regardless of their perceptual salience. Experiments 1 and 2 therefore provided compelling evidence that, in a complex multidimensional categorization task, selectively attending to diagnostic stimulus features can enhance their processing. Experiment 3 examined whether the allocation of attentional resources to stimulus features in the categorization task occurred prior to or during stimulus presentation. In the test phase of the categorization task, stimuli were presented randomly in one of the four corners of the screen, preventing attention from being directed to the expected presentation location of diagnostic features. The results of Experiment 3 were the same as those in Experiments 1 and 2. That is, stimulus features were processed at different rates in categorization and matching, with the ordinal pattern of feature processing in the categorization task predicted by feature diagnosticity, not by feature salience. The mechanism controlling the allocation of attentional

resources to stimulus features therefore operated after stimulus presentation.

Combined, the three experiments demonstrate that feature-processing rates in categorization are not determined simply by perceptual salience. Rather, the perceptual processing of stimulus features can be prioritized, with more diagnostic stimulus features being selectively attended and processed. Although other categorization studies have reported an influence of selective attention on perceptual processing, these effects have been demonstrated only in certain limited conditions, such as when a single dimension was relevant for categorization (Maddox, 2001; Maddox & Bogdanov, 2000; Maddox & Dodd, 2003). Clearly, selective attention can also influence perceptual processing in more complex categorization tasks in which information from multiple dimensions is required for accurate categorization.

Our findings extend those of Carrasco and McElree (2001) by showing that attention can accelerate the rate of perceptual processing of stimulus features, not just of whole stimuli. Furthermore, prioritization of processing does not depend on cuing the stimulus feature (Carrasco & McElree, 2001; Maddox et al., 2002). Instead, attention is guided by the learned association between stimulus features and category diagnosticity. Whether this guidance of attention is under conscious control or is automatic is unclear. The guidance mechanism can operate after stimulus onset, suggesting a flexible mechanism that uses physical characteristics of stimulus features (e.g., color, size, shape, etc.) to guide attention.

The results of our experiments contrast with previous findings, which have suggested that, when categorization tasks are complex and require information integration from multiple features, attention influences decision processes but not perceptual processes (Lamberts, 1995, 1998; Maddox, 2001; Maddox & Bogdanov, 2000; Maddox & Dodd, 2003). In Maddox and colleagues' experiments, stimuli always comprised two continuous dimensions. In the decisional selective attention conditions, only one dimension was relevant for categorization, and reduced perceptual variability along the attended dimension was observed. For other category structures, information from both dimensions had to be integrated in order to categorize stimuli correctly, and no perceptual effects of attention were observed. However, the stimulus dimensions did not differ in their diagnosticity. Lamberts (1995, 1998) did manipulate dimension diagnosticity but also found no effects of attention on perceptual processing. In the introduction to the present article, we highlighted several reasons why Lamberts's (1995, 1998) experiments may not have shown an effect of dimension diagnosticity. Each of these was addressed in the present study. The new methodology used four signal intervals instead of two, building up a much richer picture about the time course of categorization. Instead of rating the perceptual salience of stimulus features, a perceptual-matching task was used to measure perceptual salience. Participants underwent more rigorous training, and only stimuli used in training were presented at test. Aside from these design differences, there were also differences in the physical compo-

sition of the stimuli. In Lamberts (1995), the stimuli were schematic drawings of faces, and in Lamberts (1998), the stimuli were images of tea pots. In both of these studies, the stimuli had additional features that were not relevant to the task, and the features relevant for categorization were spatially arranged in a triangular pattern. In the experiments presented here, the stimuli comprised three spatially separated, vertically arranged features, all of which were relevant for categorization and differed in color, size, and shape. It is possible that this spatial composition, with clearly separable object parts, facilitated selective prioritization of individual stimulus features (Biederman, 1987; Marr & Nishihara, 1978; Vecera, Behrmann, & McGoldrick, 2000). Understanding the physical properties of stimulus features that facilitate prioritization of processing remains an interesting avenue for future research.

AUTHOR NOTE

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