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Fast categorization of stimuli with multivalued dimensions

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The extended generalized context model's (EGCM's) ability to account for the time course of categorization of stimuli with multivalued dimensions was tested in two experiments. In each experiment, the participants were first trained to classify stimuli (semicircles of variable size with a radial line of variable orientation) into two categories. In the subsequent transfer stage, they categorized a set of transfer stimuli. The time available on each transfer trial was manipulated. Responses had to be given within 400 msec, within 700 msec, or without time pressure. Different category structures were used in Experiments 1 and 2. The results of both experiments showed reliable effects of response deadline. The EGCM accounted for the data and performed consistently better than an alternative model.

Perceptual categorization is a complex process. It involves the perceptual processing of a stimulus, and a comparison of the stimulus representation with category information stored in memory. The result of this comparison is used in the subsequent decision process (see, e.g., Lamberts, 1995b). Often, the time available for carrying out this two-step process is limited. Many category decisions need to be made very quickly. A tremendous variety of activities requires fast categorization of many objects in the environment. Several studies indicate that time limitations can have strong effects on categorization (Lamberts, 1995a, 1995b; J. D. Smith & Kemler Nelson, 1984; Ward, 1983). In this article, we will review and further test a recent theory of categorization under time pressure.

In order to understand how response time affects perceptual categorization, a theory is needed that provides an explicit account of the time course of categorization. The extended generalized context model (EGCM; Lamberts, 1995a, 1995b) is intended as a general account of perceptual processing and decision making in categorization. The EGCM is derived from Nosofsky's (1986) generalized context model (GCM). The EGCM is an exemplar model, in which it is assumed that category learning involves the storage of instances in memory. After learning, categorization depends on the similarity of a stimulus and the exemplars in memory. These similarity computations and the perceptual processes that precede them are assumed to be time consuming. The different dimensions of a stimulus need to be processed before they can be included in the similarity computations. At any given time after stimulus presentation, the similarity between a stimulus and a stored exemplar will depend on the stimulus dimensions that are processed perceptually and taken into account in the computation. Therefore, the EGCM's similarity notion is time dependent. As in the GCM, similarity is assumed to be a function of the distance between stimuli:

$$s_{ij}(t) = \exp\left[-c\left(\sum_{p=1}^{P} \mathrm{inc}_p(t)\, u_p\, |x_{ip} - x_{jp}|^r\right)^{\frac{q}{r}}\right], \quad (1)$$

in which $s_{ij}(t)$ is the similarity between stimulus i and stored exemplar j at time t, c is a generalization value, $\mathrm{inc}_p(t)$ is a binary value that indicates whether dimension p has been included (1) or not (0) at time t, u_p is the utility value of dimension $p (0 \leq u \leq 1, \Sigma u = 1)$, and x_{ip} and x_{jp} are the values of the stimulus and the stored exemplar on dimension p. The type of distance metric is defined by r (city block if $r = 1$, Euclidean if $r = 2$), and q defines whether the relation between distance and similarity is exponential ($q = 1$) or Gaussian ($q = 2$). The utility value of a dimension reflects the importance of that dimension in the similarity computation. The generalization value c determines the steepness of the function that relates similarity to the number of discrepancies between the representations (see Lamberts, 1994; L. B. Smith, 1989).

Similarity is related to processing time through the inclusion indicator value $\mathrm{inc}(t)$. The probability density that a dimension is included in the similarity computation at time t is given by the exponential function:

$$f_p(t) = q_p \exp(-q_p t), \quad (2)$$

in which q_p is the *inclusion rate* of dimension p. Inclusion rates are determined by perceptual salience, which depends on the physical characteristics of a stimulus dimension (Lamberts, 1995a). Highly salient dimensions have a higher inclusion rate than do less salient dimensions. The

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probability that the dimension is included at or before t is called the *cumulative inclusion probability*, which (after integration over time of the exponential density function) is equal to

$$i_p(t) = 1 - \exp(-q_p t). \tag{3}$$

The similarity information forms the basis of the category membership decision, which is made in the next step of the categorization process. In the EGCM, the probability that stimulus i is assigned to Category J is given by

$$P(R_J \mid S_i) = (1-g)\frac{b_J \sum_{j \in C_J} s_{ij}}{\sum_{K=1}^{m}(b_K \sum_{k \in C_K} s_{ik})} + \frac{g}{m}, \tag{4}$$

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 ($\Sigma b = 1$), g is a guess rate ($0 \leq g \leq 1$), and the index $j \in C_J$ refers to all stored exemplars that belong to Category J.

The EGCM is always applied to response proportions that are obtained after aggregation across trials. In applying the model to such data, the probability of occurrence of each possible inclusion pattern is computed, using the cumulative inclusion probabilities of the different dimensions. For each stimulus, the choice probability that corresponds to each inclusion pattern is computed as well (using Equation 4), and the mathematical expectation of the choice probabilities for a stimulus is the value predicted by the model for that stimulus.

In the EGCM, the total processing time on a categorization trial corresponds to the sum of the duration of the perceptual processing stage (t) and the residual time (t_{res}). The residual time is the combined duration of a "dead time" period immediately after stimulus presentation (during which the inclusion probability of all dimensions is 0), and of the decision stage:

$$RT = t + t_{\text{res}}. \tag{5}$$

We will not discuss the factors that determine the time course of the decision stage in this article (see Lamberts, 1995b, for a detailed discussion). In all the analyses that follow, we will assume that the residual time is constant across stimuli.

Recently, Lamberts (1995a) has carried out three experiments in which the participants performed binary classifications under time pressure. The stimuli in these experiments were schematic drawings of faces, which varied on four binary dimensions. The experiments comprised two stages. First, the participants were trained until they could classify all stimuli in the training set correctly. Next, they classified a set of transfer stimuli. In the transfer stage, processing time was restricted by response deadlines of variable duration. There was also a control condition, without a deadline. On a typical trial with a response deadline, the stimulus would appear, and the participant had between 600 and 1,500 msec (depending on the condition) to produce a response. The results showed strong deadline effects. If little time was available, responses generally became less consistent and tended toward chance. However, the effects of the response deadlines differed strongly between stimuli. The classification of certain stimuli was hardly affected by the deadline manipulation at all, whereas other stimuli yielded very different response patterns at different deadlines. The preferred category assignment of some transfer stimuli even reversed when a short deadline was imposed. This interaction between stimulus and deadline ruled out an interpretation of the results in terms of differential guessing. The EGCM was applied to the response proportions. In the model applications, it was assumed that the deadline manipulation affected the duration of the perceptual processing stage. The model provided a very accurate account of the deadline effects in the three experiments. For instance, the model correctly predicted that the most salient stimulus dimensions dominated categorization decisions at the shortest deadlines. This prediction follows directly from the dimensional inclusion mechanism, because salient dimensions have the highest inclusion rates. After a short processing time, only the salient dimensions will have a reasonably high inclusion probability, whereas the nonsalient dimensions are less likely to have been processed.

These results were replicated by Lamberts (1995b), using a different procedure for limiting processing time. Instead of predictable deadlines, unpredictable response signals were used to induce fast responses. This manipulation ruled out systematic strategy differences between conditions. The results from these experiments were very similar to those obtained with predictable deadlines.

The purpose of the research in this article was to provide further tests of the EGCM. A limitation of the experiments in Lamberts (1995a, 1995b) is that the stimuli had only binary dimensions. It is not self-evident that the EGCM can account for the time course of categorization of stimuli with multivalued or continuous dimensions. It is possible that the time course of early processing of such stimuli differs considerably from that of stimuli with binary dimensions. In the case of binary dimensions, the perceptual information about each dimension needs to be processed only to the point at which identity or difference from the values of stored exemplars can be established. When dimensions can have many values, and when the category decisions can depend on small value differences, the representational demands increase. Creating a representation of a stimulus dimension that preserves, at least, order is presumably a more complex process than creating a representation that preserves only identity. To test whether the EGCM can account for the processing of multivalued dimensions, we carried out two experiments on fast categorization of stimuli with multivalued dimensions, and we applied the EGCM to the results. To limit available processing time, we used a deadline procedure similar to that in Lamberts (1995a).

EXPERIMENT 1

The stimuli in Experiment 1 were semicircles with a radial line (see Figure 1), like those previously used by Nosofsky (1986, 1989) and others (e.g., Ashby & Lee, 1991). The stimuli varied on two dimensions: the size of the semicircle and the orientation of the radial line. These dimensions are usually assumed to be perceptually separable (see Ashby & Lee, 1991). The category structure is shown in Table 1. This structure corresponds to the "diagonal" structure in Nosofsky (1986). Each stimulus dimension had four possible values. After an initial training stage, the participants categorized the stimuli under a 400-msec response deadline, a 700-msec deadline, and without deadline.

Method

Participants. Four graduate students from the University of Birmingham, 2 men and 2 women, participated in the experiment. They were paid £9.

Apparatus and Stimuli. The Experiment was controlled by an Elonex PC-466 computer with a Vale EC 33-cm SVGA color monitor, using a display mode with 1,024 pixels horizontally and 800 pixels vertically. Responses were registered by means of two microswitches connected to the computer's parallel port. The stimuli were semicircles that varied in size and angle of orientation of a radial line (see Figure 1). Sixteen stimuli were constructed from the orthogonal combination of four levels of semicircle radius (178, 212, 246, and 280 pixels, corresponding to 41, 48, 55, and 62 mm, respectively), and four levels of radial line orientation (45°, 54°, 63°, and 72°). The stimuli appeared yellow on a black background, in the center of the screen. The participants sat approximately 1.5 m from the screen in a dark room. At this distance, individual pixels were not distinguishable, so that the semicircles and the radial lines appeared completely smooth (otherwise, the jaggedness of the radial line might have provided a cue as to its orientation).

Design and Procedure. Each participant attended three sessions. Each session consisted of a training stage followed by a transfer stage. The first session was devoted to practice. Only the training data from this session were analyzed. The transfer results from the first session were discarded. During training, eight stimuli were presented repeatedly. The structure of the training stimuli is shown in Table 1. Within each block of eight, the training stimuli occurred in random order. The participants' task was to categorize each stimulus as a member of Category A or B by pressing one of the two response buttons. The assignment of the buttons to the categories was randomized across participants. On each trial, a semicircle appeared on the screen and remained present until a response was given. After each response, auditory correct–incorrect feedback was presented. Training continued until no mistakes were made on three successive blocks.

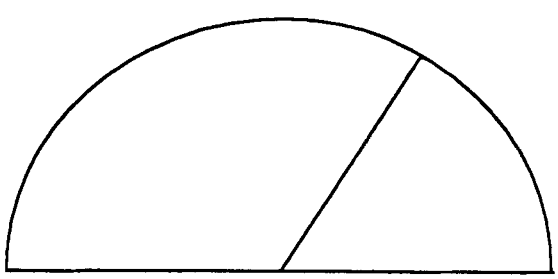

Figure 1. Sample stimulus in Experiment 1.

Table 1
Structure of Stimuli in Experiment 1

	Angle			
Size (mm)	45°	54°	63°	72°
62	A1	B1	T5	T7
55	A2	T3	B2	T8
48	T1	A3	T6	B3
41	T2	T4	A4	B4

Note—The letter in each stimulus code indicates category membership. The stimuli with prefixes A and B were training stimuli from Categories A and B, respectively. The stimuli prefixed with T are transfer stimuli.

In the transfer stage, the time available for categorization was manipulated, using a deadline procedure similar to that in Lamberts (1995a). In the first deadline condition, the participants had to respond within 400 msec of stimulus presentation. In the second deadline condition, the time available was 700 msec. In the third, no-deadline (ND) condition, response time was unlimited. When a deadline applied, the transfer stimulus remained present on the screen until a category response was given or until the deadline passed, whichever was sooner. A loud tone sounded for 500 msec if the deadline passed without a response. In the ND condition, the stimuli remained on the screen until a response was given. No correct–incorrect feedback was provided in the transfer stage. The participants were instructed to respond within the deadlines while maintaining the highest possible level of accuracy. In each session, three blocks of 192 transfer trials were presented (yielding a total of 576 trials per session), with one block for each deadline condition. The order of presentation of the blocks was randomized. Before each block, a message appeared on the screen indicating which deadline applied to that block. Within each block, the 16 transfer stimuli obtained by orthogonal combination of the two dimensions were presented 12 times, in random order.

Results and Discussion

Training. Only the training data from the first session were analyzed. The training stages of Sessions 2 and 3 were always much shorter. Across participants, the average number of eight-trial blocks needed to attain the learning criterion (three consecutive blocks without error) was 42, with a standard deviation of 11.20. The mean error frequencies across participants for the eight training stimuli are shown in Table 2. A repeated-measurements analysis of variance (ANOVA)[1] on the error frequencies showed a reliable effect of stimulus [$F(7,21) = 4.52$, Huynh-Feldt $\varepsilon = .709$, $MS_e = 21.08$, $p < .05$]. The error frequencies for Stimuli A4 and B1 were relatively high. This is probably due to the structure of the categories. In the stimulus space shown in Table 1, A4 and B1 are the only stimuli that have more adjacent training stimuli from the other category than from their own category. The neighbors of A4 are B3, B4, and A3, and the neighbors of B1 are A1, A2, and B2. If confusion with neighbors occurs (as one can expect early in training), the error frequencies for A4 and B1 are bound to be relatively high compared with those for the other stimuli. The same argument can be used to explain the intermediary error frequencies for A1 and B4. These two stimuli have one neighbor from each category.

Table 2
Mean Error Frequencies in Training Stage of Experiment 1, as a Function of Stimulus

Stimulus	Error Frequency
A1	12.8
A2	5.5
A3	9.0
A4	20.0
B1	12.0
B2	8.8
B3	4.5
B4	8.5

Transfer. The proportions of late responses for the transfer stimuli in the two deadline conditions are shown in Table 3. The total proportion of late responses was .19 in the 400-msec deadline condition and .02 in the 700-msec condition. As might be expected, there was a reliable effect of deadline on these proportions [$F(1,3) = 19.40$, $MS_e = .042$, $p < .05$; Huynh-Feldt ε not determined]. There was no reliable effect of stimulus, and no interaction between deadline and stimulus.

The mean reaction times (RTs) on trials with responses within the deadline are also shown in Table 3. A two-way ANOVA on the RTs only showed a reliable main effect of deadline [$F(2,6) = 15.08$, Huynh-Feldt $\varepsilon = .540$, $MS_e = 316{,}584$, $p < .05$], indicating that the deadline manipulation was successful in producing clear RT differences between the conditions.

The proportions of Category A responses are shown in Figure 2. An ANOVA on these proportions yielded a significant effect of stimulus [$F(15,45) = 21.91$, Huynh-Feldt $\varepsilon = .339$, $MS_e = .046$, $p < .001$] and a significant interaction between deadline and stimulus [$F(30,90) = 6.13$, Huynh-Feldt $\varepsilon = .527$, $MS_e = .013$, $p < .001$]. The response proportions tended to be more extreme (closer to 0 or 1) as more time was available. A comparable interaction between stimulus and RT occurred in all previous experiments on fast categorization (Lamberts, 1995a, 1995b).

We applied the EGCM to the observed response proportions. For modeling purposes, the four values of each stimulus dimension were encoded as 1, 2, 3 and 4, respectively. Preliminary analyses showed that the combination of a Euclidean distance metric ($r = 2$) and a Gaussian

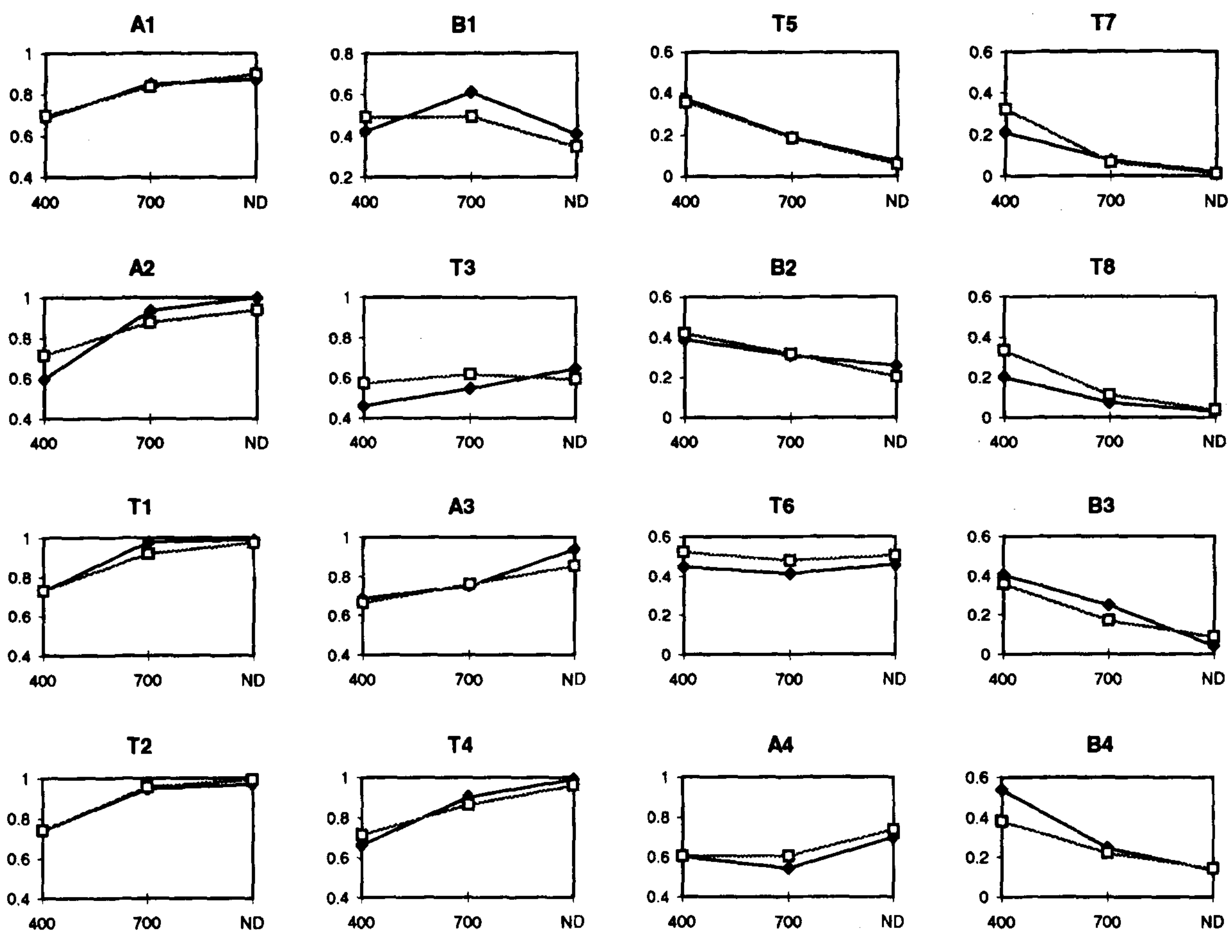

Figure 2. Observed and predicted proportions of Category A responses in Experiment 1. Observed proportions are shown as black diamonds; predicted proportions, as white squares. The predictions were generated by the extended generalized context model.

Table 3
Proportions of Late Responses and Mean Reaction Times (RT, in Milliseconds) as a Function of Stimulus and Deadline Condition in Experiment 1

	Deadline Condition					
	400 msec		700 msec		No Deadline	
Stimulus	Late	RT	Late	RT	Late	RT
A1	.18	322	.02	468	—	913
A2	.18	321	.03	452	—	784
A3	.25	318	.03	447	—	1,081
A4	.18	311	.02	468	—	916
B1	.21	317	.06	479	—	1,093
B2	.20	320	.02	463	—	812
B3	.18	328	.00	438	—	733
B4	.15	316	.03	473	—	703
T1	.13	318	.01	445	—	756
T2	.17	314	.00	453	—	723
T3	.23	325	.01	481	—	1,224
T4	.20	323	.03	456	—	799
T5	.22	321	.00	459	—	784
T6	.21	320	.06	472	—	1,002
T7	.16	325	.03	442	—	609
T8	.17	324	.01	445	—	631
M	.19	320	.02	459	—	848

decay function ($q = 2$) yielded the best fits to the data, confirming previous results with similar stimuli (e.g., Nosofsky, 1986). In all analyses in this article, a Euclidean–Gaussian similarity definition was applied.

Six parameters of the EGCM were estimated: a utility value u for the size dimension (which also determines the utility value for angle, because these two values sum to 1), a generalization value c, an inclusion rate q for size and an inclusion rate for angle, a bias value b, and a residual time parameter t_{res}. We assumed that all guess rates were 0. In each deadline condition, the duration of the perceptual processing stage was assumed to equal the observed mean RT (in milliseconds) in that condition minus the estimated residual time. As such, the same parameters applied to all deadline conditions. According to the model, all differences between these conditions are the exclusive result of differences in perceptual processing time. Parameter estimation was based on a maximum-likelihood criterion (see Lamberts, 1994). The model accounts for 94.6% of the variance in the response proportions [$\ln(L) = -164.343$]. The model's predictions are shown in Figure 2, and the parameter values are listed in Table 4. All the main trends in the data are accounted for. Six of the eight training stimuli (A1, A2, A3, B2, B3, and B4) yielded regular response patterns, with increasing accuracy for longer response times. The model's predictions for these stimuli are very accurate. The response patterns for B1 and A4 were different (these were the two stimuli that produced many errors in training). For B1, responses were less accurate in the 700-msec condition than in the 400-msec and ND conditions. The model does not predict a disadvantage for the 700-msec condition, although its predicted values are still fairly close to the observed values. The results for A4 show only a small difference in accuracy between the three deadline conditions. The EGCM predicts a similar response pattern.

The response proportions for the eight transfer stimuli are also explained well by the model. The diagonal arrangement of the training stimuli divides the stimulus space in two main regions. The transfer stimuli in the bottom left-hand corner (T1, T2, and T4) are consistently placed in Category A, as predicted by the model. The deadline effect for these stimuli is also predicted. The transfer stimuli in the upper right-hand corner (T5, T7, and T8) are all categorized as members of the B category. Finally, the two transfer stimuli in the central area of the stimulus space (T3 and T6) yielded no consistent choice for either category, as predicted.

The relatively high utility value for the angle dimension is optimal for this category structure, because it will tend to maximize the number of correct responses (see Nosofsky, 1986). The inclusion rates for the two dimensions are quite similar. This probably indicates that both dimensions are about equally salient (Lamberts, 1995a, 1995b). The estimated residual time (260 msec) corresponds closely to estimates from previous experiments (Lamberts, 1995a, 1995b).

Table 5 presents an overview of the occurrence probabilities of each inclusion pattern in the three deadline conditions. In the 400-msec condition, the estimated perceptual processing time is 61 msec (321 msec average RT, minus 260 msec residual time). In this condition, the probability that both dimensions have been considered in the similarity computations is only .22. In the 700-msec condition (with an estimated perceptual processing time of 199 msec), the probability of inclusion of both dimensions increased to .76, and in the ND condition both dimensions were almost always included, as one would expect.

So far, the EGCM has only been applied to response proportions that were obtained after averaging across subjects. Recently, Ashby, Maddox, and Lee (1994) have demonstrated that a similarity-choice model (such as the EGCM) can provide excellent fits to averaged data, without necessarily being able to fit the data from individual subjects. To verify that the EGCM's success is not an artifact of averaging, we applied the model to the choice proportions from individual subjects. For each subject's data, the same six parameters were estimated as for the average data. Table 6 contains an overview of the estimated

Table 4
Estimated Parameter Values for the EGCM, Experiment 1

Parameter	Value
u(size)	.292
[u(angle)]	[.708]
c	1.801
q(size)	0.00959
q(angle)	0.01133
b	.548
t_{res} (msec)	259.9

Note—The utility value for angle (shown between brackets) was derived from the estimated utility value for size.

Table 5
Occurrence Probabilities of Different Inclusion Patterns as a Function of Deadline

		Deadline Condition		
inc(size)	inc(angle)	400 msec	700 msec	No Deadline
0	0	.279	.015	.000
0	1	.278	.133	.004
1	0	.222	.089	.001
1	1	.221	.763	.995

parameter values for the four subjects. The model fitted the individual data well, taking into account that the number of observations on which each proportion was based was four times smaller than for the aggregated proportions. It seems unlikely, therefore, that the EGCM's good aggregate fit is the result of averaging.

In summary, the results from Experiment 1 show that the EGCM can account for deadline effects in the categorization of stimuli with multivalued dimensions. The experiment thus provides further support for the EGCM as a model of the time course of categorization.

EXPERIMENT 2

Although the EGCM can account well for the results from Experiment 1, alternative interpretations of the data should be considered. In particular, it is possible that the deadline effects can be explained in terms of differences in guess rates, without the need to assume a dimensional inclusion process. On such an account, the participants would guess more under shorter deadlines (see Lamberts, 1995a, 1995b). Differential guessing could produce a general fan-out of the response proportions with increasing deadline.

To test this alternative account, we applied a version of the EGCM to the data from Experiment 1, in which all cumulative inclusion probabilities were equal to 1 in all conditions (effectively canceling out the inclusion mechanism), and in which guess rates were allowed to vary freely between conditions. With six parameters (u, c, b, and three guess rates), the model fitted the data only slightly worse than the standard EGCM [$\ln(L) = -164.756$]. The estimated guess rates were .58, .11, and 0 in the 400-msec, 700-msec, and ND conditions, respectively. Therefore, a guessing interpretation of the results cannot be ruled out. For the category structure in Experiment 1, the EGCM with the inclusion mechanism and the guessing model make very similar predictions.

In previous research on fast classification, a clear differentiation between a guessing account and the EGCM was obtained with category structures that were irregular (Lamberts, 1995a). Therefore, we used a different category structure in Experiment 2. The stimuli are shown in Table 7. One stimulus (B4) is an exception within its category. In the stimulus space, it is surrounded by exemplars from Category A. The other members of Category B are located in the opposite corner. As a result, B4 is more similar to members from the other category than to members from its own category. Although it was impossible to predict how the participants would respond to this structure under time pressure (even small changes in parameter values can lead to very different response patterns), we expected that the irregular structure would bring about significant differences between the EGCM and the guessing account. According to the guessing account, deadline effects exhibit a regular pattern for all stimuli. The more guessing occurs, the more all response proportions will approach the .5 chance level. However, exceptional stimuli can elicit irregular responses under time pressure (Lamberts, 1995a). Their category assignment can even reverse, depending on the available time. In previous experiments, the EGCM accounted well for such irregularities and thereby clearly outperformed an alternative guessing account (Lamberts, 1995a).

Method

Participants. Three graduate students from the University of Birmingham, 2 men and 1 woman, participated in the experiment. They were paid £9. Although all the participants had prior experience with RT experiments, none of them had taken part in Experiment 1.

Apparatus and Stimuli. The equipment and stimuli were the same as those used in Experiment 1.

Design and Procedure. The design and procedure for this experiment were very similar to those for Experiment 1. Each participant attended three sessions, and each session consisted of a training stage followed by a transfer stage. The first session was devoted to practice; only the training data from this session were analyzed. The structure of the training stimuli is shown in Table 7. Three training stimuli belonged to Category A, and four stimuli belonged to Category B. The transfer task was identical to that in Experiment 1. All combinations of size and angle occurred repeatedly, under a 400-msec response deadline, a 700-msec deadline, or without deadline. In each session, three blocks of 192 trials were presented (one block for each deadline condition).

Results and Discussion

Training. The mean error frequencies per stimulus in the first training session are shown in Table 8. Because 1 participant produced hardly any B responses in the first training blocks, the stimuli in Category A have higher error frequencies. Of the Category B stimuli, B4 (the exception) yielded the highest error frequency, as expected.

Table 6
Estimated Parameter Values of EGCM for Individual Subjects' Response Proportions in Experiment 1

	Subject			
Parameter	1	2	3	4
u(size)	.28	.16	.70	.10
[u(angle)]	[.72]	[.84]	[.30]	[.90]
c	1.569	1.421	1.915	1.759
q(size)	.0053	.0114	.2090	.2831
q(angle)	.0394	.0112	.0101	.0113
b	.275	.689	.422	.754
t_{res} (msec)	308.9	291.1	260.5	260.4
R^2	.88	.86	.88	.85

Note—The utility value for angle (shown between brackets) was derived from the estimated utility value for size.

Table 7
Structure of Stimuli in Experiment 2

Size (mm)	Angle 45°	54°	63°	72°
62	T1	T4	B3	T8
55	B2	B1	T6	T9
48	T2	T5	A2	A1
41	T3	A3	T7	B4

Note—The letter in each stimulus code indicates category membership. The stimuli with prefixes A and B were training stimuli from categories A and B, respectively. The stimuli prefixed with T are transfer stimuli.

Table 8
Mean Error Frequencies in Training Stage of Experiment 2, as a Function of Stimulus

Stimulus	Error Frequency
A1	10.0
A2	14.3
A3	11.3
B1	5.7
B2	3.0
B3	4.7
B4	8.0

Transfer. In Table 9, the proportions of late responses and mean RTs are shown. An ANOVA of the proportions of late responses yielded no reliable effects. There was only a nonreliable trend toward more late responses at the shortest deadline [$F(1,2) = 10.75, p = .08$]. The ANOVA of the RTs in the three deadline conditions only showed a reliable effect of deadline [$F(2,4) = 14.26$, Huynh-Feldt $\varepsilon = .783$, $MS_e = 352{,}354$, $p < .05$]. There was no stimulus effect [$F(15,30) = 1.20, p = .32$] and no interaction between deadline and stimulus ($F < 1$).

The proportions of Category A responses for each stimulus at the three deadlines are shown in Figure 3. Analysis of these proportions yielded a reliable main effect of stimulus [$F(15,30) = 4.29$, Huynh-Feldt $\varepsilon = .208$, $MS_e = .067, p < .05$] and a reliable interaction between deadline and stimulus [$F(30,60) = 3.50$, Huynh-Feldt $\varepsilon = 1.000$, $MS_e = .016$, $p < .001$]. For the training stimuli in Category A (A1, A2, and A3), the familiar fan-out effect occurred, with most consistent responses in the ND condition. The same was true for the "regular" members of Category B (B1, B2, and B3). The exceptional Stimulus B4 showed a different and unexpected pattern, however. At the 400-msec deadline, responses were at chance level (.49). In the 700-msec condition, they became less accurate, with a majority of A responses (.72). In the ND condition, the proportion returned to chance level again (.52). A very similar pattern occurred for Transfer Stimulus T7, which is located in the same area of the stimulus space but was not presented in the training stage. For the other transfer stimuli, the results were generally regular.

We applied the same two versions of the EGCM to the response proportions as in the analysis of Experiment 1. The "standard" six-parameter version, with a Euclidean metric and a Gaussian decay function, produced the predicted values shown in Figure 3. The best fitting parameter values are shown in Table 10. The model accounted for 90.5% of the variance in the response proportions [$\ln(L) = -134.363$].

The estimated utility values are different from those in Experiment 1, with size receiving a higher utility value than angle. For the category structure in Experiment 2, this utility distribution is close to optimal, because information about size alone is sufficient to classify all training stimuli correctly, except for B4. The angle dimension is less predictive for category membership. The inclusion rates for size and angle were similar, and in the same range as the values estimated in Experiment 1. The estimated residual time was also very close to the value from Experiment 1. These correspondences across experiments are reassuring, because they suggest that the estimated values of the model parameters are robust and meaningful. The occurrence probabilities of the four possible inclusion patterns are shown in Table 11. Again, the values correspond very well to what would be expected. Both dimensions were almost always included in the ND condition. In the 400-msec condition, the probability that neither dimension was processed was almost .70.

Table 9
Proportions of Late Responses and Mean Reaction Times (RT, in Milliseconds) as a Function of Stimulus and Deadline Condition in Experiment 2

	Deadline Condition					
	400 msec		700 msec		No Deadline	
Stimulus	Late	RT	Late	RT	Late	RT
A1	.14	296	.14	459	—	1,035
A2	.19	310	.08	464	—	996
A3	.29	298	.08	469	—	1,012
B1	.22	308	.07	442	—	846
B2	.29	306	.07	438	—	882
B3	.15	294	.03	457	—	782
B4	.15	310	.10	452	—	967
T1	.17	308	.04	447	—	751
T2	.19	304	.10	466	—	961
T3	.17	303	.10	470	—	1,025
T4	.15	301	.04	435	—	718
T5	.17	304	.06	456	—	1,001
T6	.22	310	.03	460	—	901
T7	.21	300	.04	485	—	1,018
T8	.21	298	.07	446	—	921
T9	.17	300	.08	468	—	974
M	.19	303	.07	457	—	925

Table 10
Estimated Parameter Values for the EGCM, Experiment 2

Parameter	Value
u(size)	.740
[u(angle)]	[.260]
c	0.939
q(size)	0.0071
q(angle)	0.0065
b	.475
t_{res} (msec)	273.6

Note—The utility value for angle (shown between brackets) was derived from the estimated utility value for size.

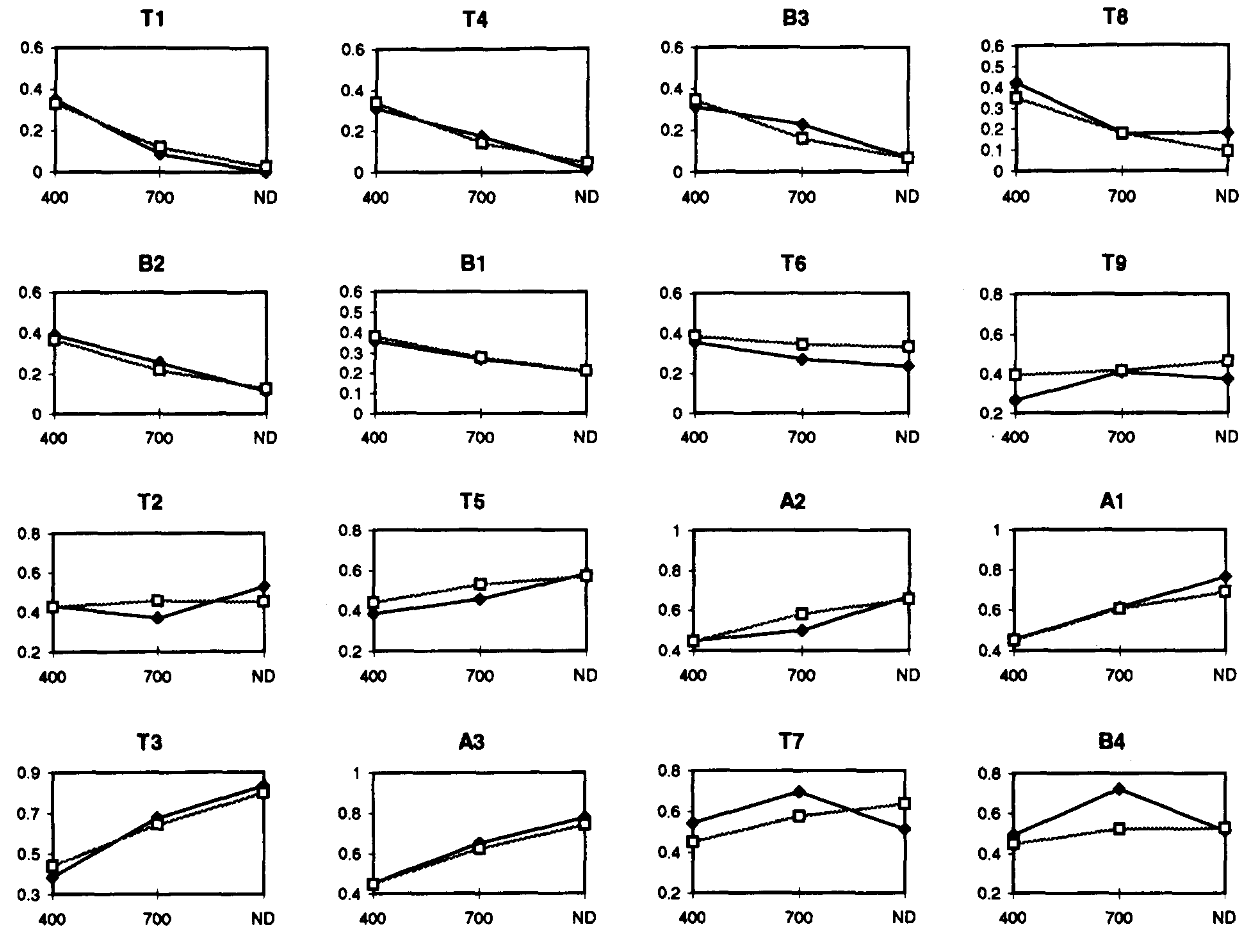

Figure 3. Observed and predicted proportions of Category A responses in Experiment 2. Observed proportions are shown as black diamonds; predicted proportions, as white squares. The predictions were generated by the extended generalized context model.

The EGCM's predictions of performance on the regular training stimuli (A1, A2, A3, B1, B2, and B3) are very accurate. However, the model does not account very well for the irregular response pattern for the exception B4. Although it is accurate for the 400-msec and ND conditions, it overestimates the proportion of B responses in the 700-msec condition. The model predicts slightly better than random responding at the 400-msec deadline, and a decrease in the proportion of Category B responses in the 700-msec and ND conditions. We tried many different versions of the EGCM, allowing variation in many combinations of parameters, but none produced the high proportion of A responses on B4 in the 700-msec condition, while still accounting well for performance on the other stimuli.

The EGCM predicts the response proportions for the nine unseen transfer stimuli with remarkable accuracy. The observed response pattern for Transfer Stimulus T7 was very similar to that for B4. The EGCM performs better on T7 than on B4. On T7, it predicts a substantial increase in the proportion of A responses in the 700-msec condition, as observed.

The alternative model with differential guessing but without the dimensional inclusion mechanism performed considerably worse than the standard EGCM [$\ln(L) = -149.175$], accounting for only 84.7% of the variance in the response proportions. The guessing model failed to account for performance on many stimuli, producing a residual sum of squares (0.303) that was almost twice as high as that of the standard EGCM (0.188).

We also applied the EGCM to the response proportions from individual participants. Table 12 contains the estimated parameter values for the 3 subjects. As in Experiment 1, the model accounted for the main patterns in

Table 11
Occurrence Probabilities of Different Inclusion Patterns as a Function of Deadline in Experiment 2

		Deadline Condition		
inc(size)	inc(angle)	400 msec	700 msec	No Deadline
0	0	.675	.081	.000
0	1	.140	.190	.010
1	0	.153	.219	.014
1	1	.032	.510	.976

Table 12
Estimated Parameter Values of EGCM for Individual Subjects' Response Proportions in Experiment 2

	Subject		
Parameter	1	2	3
u(size)	.96	.74	.61
[u(angle)]	[.04]	[.26]	[.39]
c	1.281	1.003	1.600
q(size)	.0030	.1211	.0015
q(angle)	.0466	.0201	.0062
b	.50	.46	.48
t_{res} (msec)	254.2	296.2	300.0
R^2	.81	.74	.67

Note—The utility value for angle (shown between brackets) was derived from the estimated utility value for size.

the individual data, but it performed slightly worse than it did on the aggregate data (as expected, given the smaller number of observations).

The main conclusion from Experiment 2 is that the EGCM's validity as a model of the time course of categorization was confirmed again. The guessing alternative was clearly rejected. As in Experiment 1, the deadline effects could be explained well by the EGCM's dimensional inclusion mechanism.

GENERAL DISCUSSION

The results from the two experiments in this article show that the EGCM can account for the effects of processing time restrictions on the categorization of stimuli with multivalued dimensions. There was no need to assume additional processes from those postulated in the standard EGCM in order to account for the experimental data. With only six parameters, and without allowing any free parameters to vary between deadline conditions, the model accurately predicted the effects of response deadlines. The estimated parameter values either were stable across the experiments (such as t_{res} or the inclusion rates), or differed in a meaningful and systematic manner (such as the utility values).

Probably, very few objects in the real world are represented entirely by binary dimensions. Many subtle distinctions between object categories (such as those between cars of different makes, or between different breeds of dogs) depend on precise metric information. The EGCM's ability to account for the time course of processing of stimuli with multivalued dimensions is important, because the model is intended as a general account of perceptual and decision processes in categorization (which includes identification as a special case, in which the number of objects equals the number of categories; cf. Nosofsky, 1989). A comparison between the experiments in this article and those in Lamberts (1995a, 1995b) does not reveal fundamental differences between the processing of binary dimensions and the processing of multivalued dimensions. On the contrary, the EGCM's ability to explain deadline effects across a wide range of stimuli suggests that the same mechanism is involved in all these cases.

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NOTE

1. For all repeated measurements ANOVAs, we report Huynh-Feldt ε values. The reported significance levels were obtained after correcting the degrees of freedom of the F statistic by ε, to safeguard against violations of the sphericity assumption (see, e.g., Kirk, 1995).

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