Appendix

Stimuli

Random Dot Shapes Creation

Random dot shapes are a modification of Posner & Keele's (1968) random dot patterns and have been commonly used in experiments in order to more easily elicit participant interest and attention (e.g. Smith et al., 2008). Random dot pattern stimuli and the associated family resemblance category structures are generated, using Turbo Pascal 7.0, by affixing nine points within a 30x30 pixel central area of a 50x50 pixel area.

Next family resemblance category members of different distortion levels are created by varying the distance of each dot from its original position in the prototype pattern. Different distortions are created by changing the probability that each dot will move within a five area space. In Area 1, the dot keeps its original position. In Area 2, the dot moves to one out of the 8 pixels immediately surrounding the original dot position. In Area 3, the dot moves to a position on the shell around the previous 8 pixels, consisting of 16 pixels. In Area 4, the dot moves to one of the positions on the third, fourth, and half of the fifth pixel shell around Areas 1-3. In Area 5, the dot moves to one of the remaining 300 pixels in a 20x20 peripheral grid outside of Areas 1-4.

Distortion level indicates the strength or weakness of family resemblance, as the algorithm will move the original dots to closer areas if they are low-level (strong family resemblance) distortions and to distant areas if they are high-level (weak family resemblance) distortions. The probability that the dots of the prototype (distortion level 0) will stay in area 1 is 1.0. See Table 1 for the remaining distortion level dot location probabilities.

Table 1. Dot location probabilities for each distortion level.

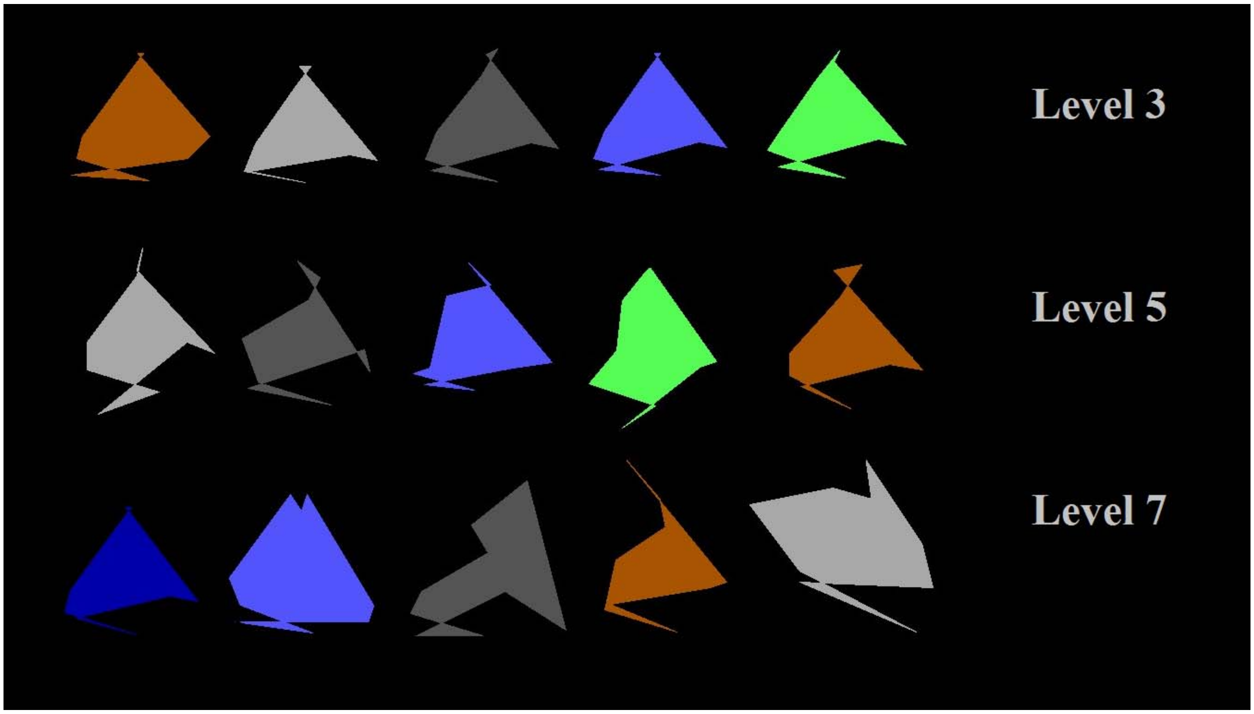
Distortion Level	Area 1	Area 2	Area 3	Area 4	Area 5
2	.75	.15	.05	.03	.02
3	.59	.20	.16	.03	.02
4	.36	.48	.06	.05	.05
5	.2	.3	.4	.05	.05
7	0	.24	.16	.3	.3

The dot patterns were magnified to three times their original size in order to make them more visible to participants. This was done by mapping each point into the center of a 3x3 pixel area, so that a pattern originally represented in a 50x50 pixel area would be displayed in an area of 150x150 pixels. Next, the random dot shapes were created by using the DrawPoly procedure in Turbo Pascal 7.0 to join successively created dots with lines. Lastly, this program added a variety of colors to the fill in the polygon shapes, to add extra appeal to the stimuli.

Random dot patterns which were designated “Randoms” and were not part of the category, were created without the use of the category prototype by random placement of nine dots in the 50x50 pixel area. No distortion algorithm was applied to the random patterns. Using an identical procedure to the one outlined above for category members, the dots of the Randoms were joined, and the same colors were filled in (See Figures 1 and 2 for the training and testing stimuli used in the experiment).

Figure 1. *A.* All category-members shown during training. The first row includes L-3 stimuli, the second row includes L-5 stimuli, and the third row includes L-7 stimuli. *B.* Examples of all non-category-members shown during training.

A.



B.

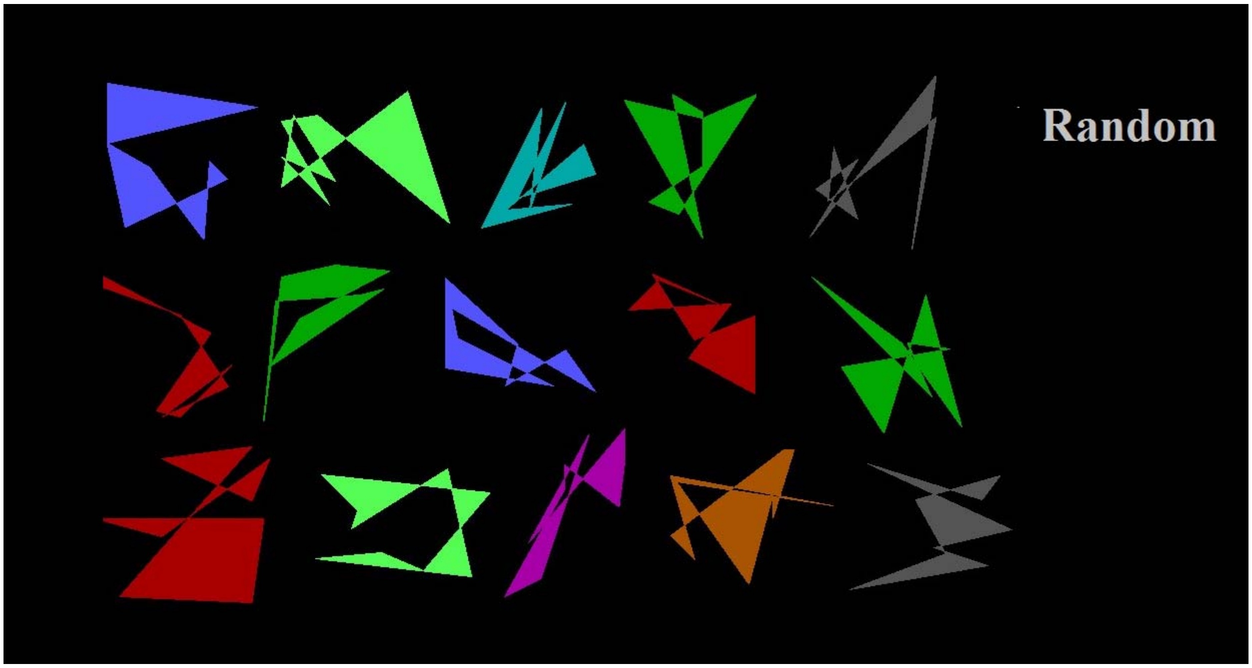
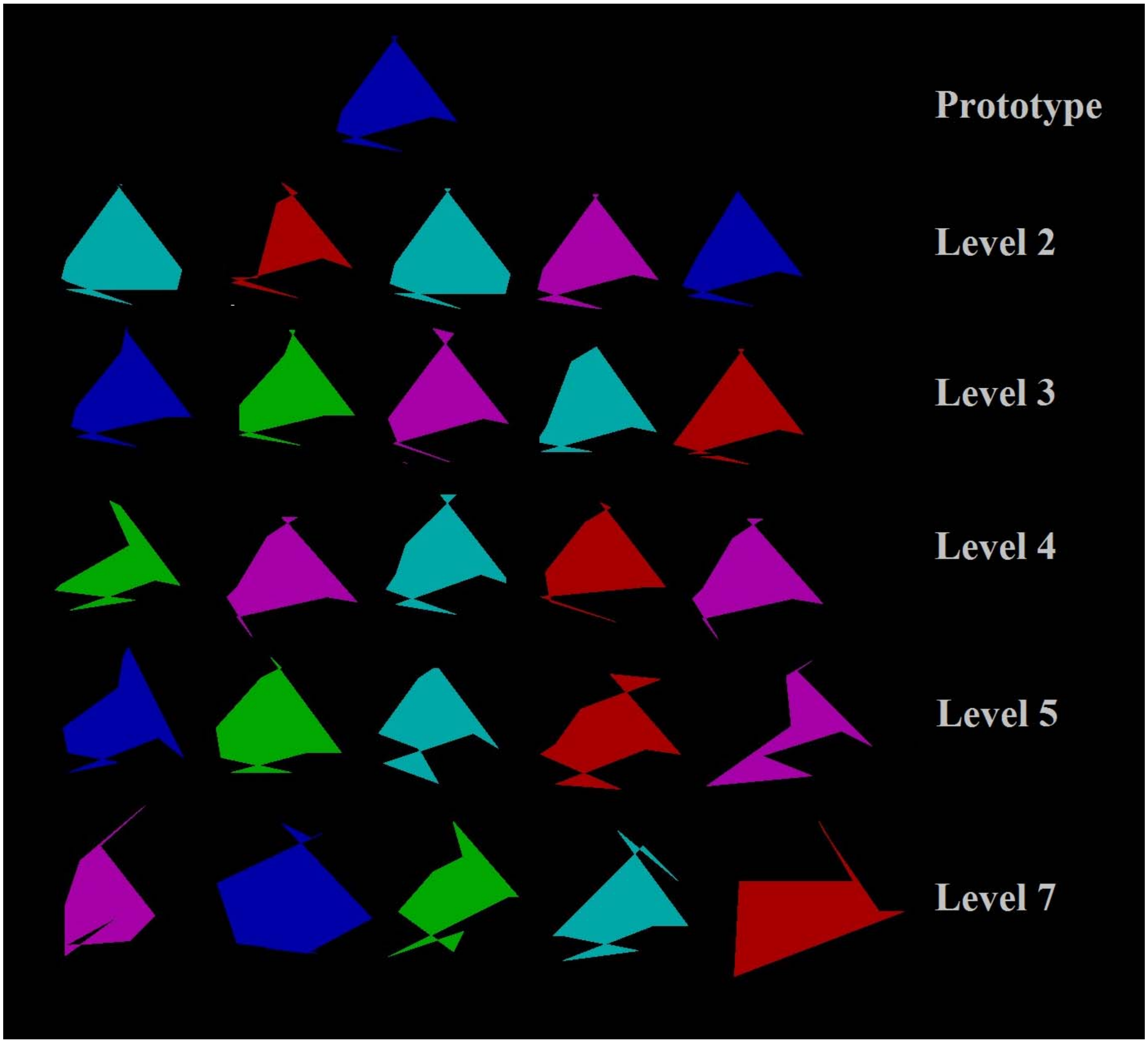
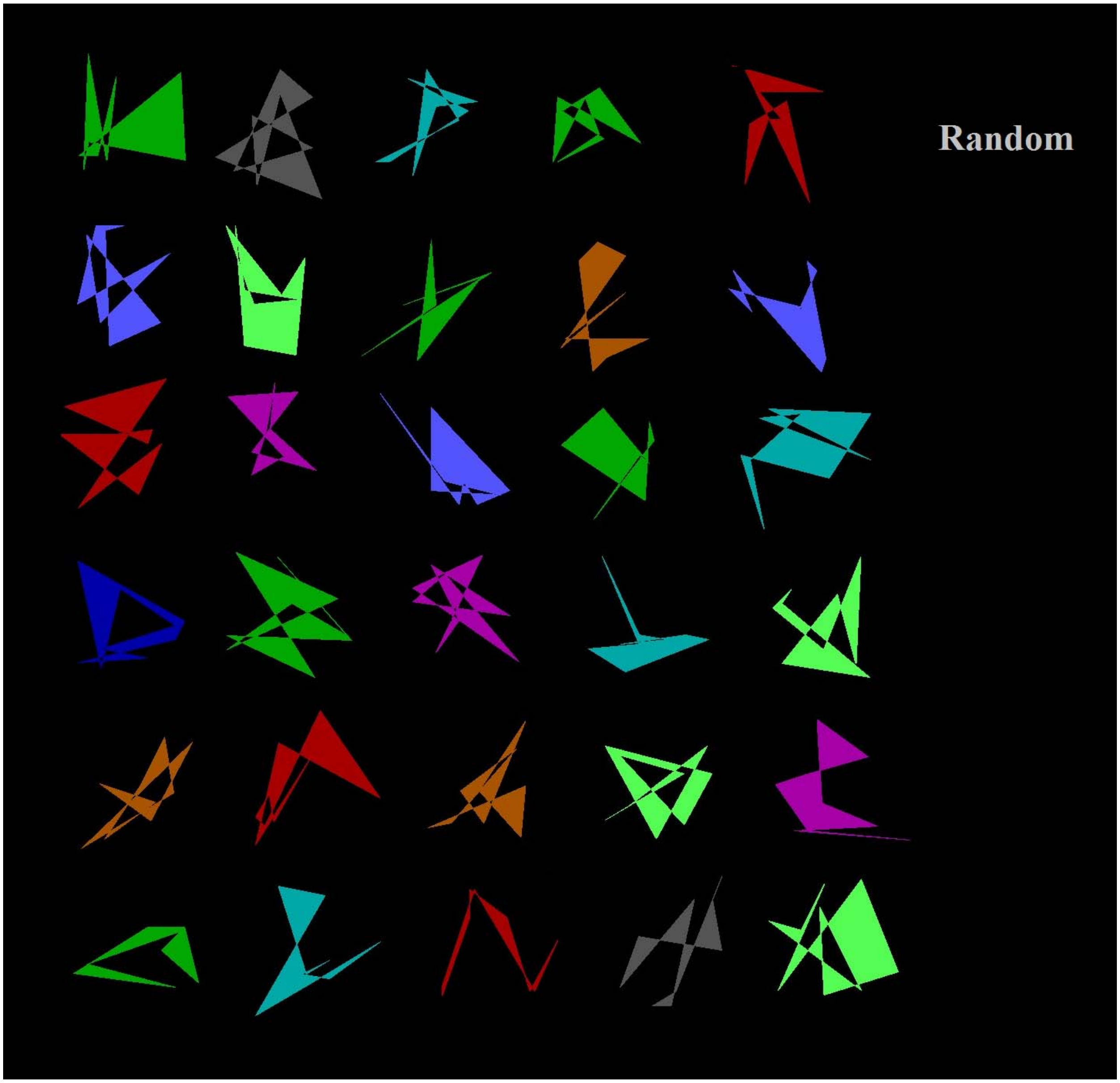


Figure 2. *A.* All category-member stimuli shown during testing. The first row includes the prototype, second L-2 stimuli, third L-3 stimuli, fourth L-4 stimuli, fifth L-5 stimuli, and the sixth L-7 stimuli. *B.* All non-category-members shown during testing.

A.



B



The Prototype Model

The prototype model assumes that individuals are comparing to-be categorized items (TBCIs) with a summary representation of the category (e.g., a prototype) in order to make category membership decisions. In this experiment, our TBCI types include the prototype, Level 2 distortion, Level 3 distortion, Level 4 distortion, Level 5 distortion, Level 7 distortion, and Randoms. Psychological similarity between TBCIs *(i)* and the prototype *(p)* are estimated by this model in order to predict the strength of category endorsement, given each item type. The values for the model equation below follow. R_{Cat} = Category Response, S_i = Given Item Type, η= Psychological Similarity, and k= criterion quantity (a proportionalizing free parameter). In simple terms, the choice rule equation (A) below states the probability of category endorsement, given the TBCI type:

(A) $$P(R_{Cat}|\, S_i) = \frac{\eta_{ip}}{\eta_{ip} + k}$$

To calculate psychological similarity (η), we used the average Pythagorean distance that corresponding dots were moved between the patterns of the two types *(i)* and *(p)* (Smith et al., 2008). This psychological distance measurement was set equal to the equation ln (1+ mean Pythagorean distance). In order to provide the most powerful estimate possible of this measure, one million samplings of each pair type were modeled to produce the values of 0.0000, 0.4497, 0.6401, 0.8687, 1.094, 1.762, and 2.8479 (Smith et al, 2008). These are the average logarithmic distances between the prototype and the prototype, Level 2 distortion, Level 3 distortion, Level 4 distortion, Level 5 distortion, Level 7 distortion, and Randoms (respectively).

Psychological similarity is an exponential-decay function of the psychological distance. In formal categorization modeling, a sensitivity parameter is often utilized to control the steepness of the decay. Therefore, the distance measures above *(d)* were translated to psychological similarity measures, for all transfer item types, by using an exponential-decay function *(e)* and incorporating a second free parameter, sensitivity *(c)*, as shown below:

$$\eta_{ip} = e^{-cd_{ip}}$$

Psychological similarity (η) was entered into the choice rule (A) above, and the probability of endorsement (model-predicted endorsement) was calculated for each item type.

Model Fitting

Standard "hill-climbing" procedures were used to find the best possible prototype model fits to the data. Hill-climbing procedures have been used reliably in categorization research, and involve seeding the model to find the best fit (e.g. Smith et al., 2008). Seeding the model is a process that refers to changing the criterion *(k)* and sensitivity *(c)* free parameters in order to produce the lowest deviation between the model predictions and actual observed participant performance for each item type.

During each instance of seeding the model, one parameter and a directional change were randomly applied, and new values replaced the old values if they produced a better fit. The directional changes were always very small (1/10,000,000 for criterion and 1/10,000 for sensitivity) and respected the upper and lower bounds of the free parameters (0.0000001 and .1 for criterion and .0001 and 10 for sensitivity). Also, at least four hill-climbing attempts (using new configurations of free parameter values) were made for every item type, to ensure that local minima did not limit the model's predictive power. Once the best fit had been determined, the sum of the squared deviations between the model predictions and the observed values and best fit values of the sensitivity (*c*), and criterion (*k*) free parameters were recorded for each participant.