

Category Learning Effects on Memory

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Abstract Category learning...

Keywords First keyword · Second keyword · More

Introduction

Methods

Participants 867 participants were recruited via Amazon Mechanical Turk (<https://www.mturk.com>). All participants were from the United States, had at least 100 approved hits, had an overall hit approval rate of at least 95%, and received \$2.00 in compensation for their participation. Data from 153 participants were excluded because of failure to learn the category (i.e., below 85% accuracy during the last 20 trials of learning, as defined in De Brigard et al. (2017)), or excessive mean response time during learning or test (greater than the mean + three standard deviations, 5.95 seconds and 5.46 seconds respectively), so data were analyzed with the remaining 714 individuals. All participants were provided informed consent in accordance with the Duke University IRB.

Materials Stimuli consisted of MATLAB (2018b)-generated flowers, used previously in De Brigard et al. (2017). These flowers vary over five features, with each feature having three possible values: number of petals (four, six, or eight), petal color (blue, green or yellow), center shape (circle, triangle, or square), center color (orange, purple, or turquoise), and number of sepals (one, two, or three). Figure 1 depicts three flowers that illustrate all possible values of the five features. All flowers were displayed on the center of the screen with a white background.

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Fig. 1 Example stimuli encompassing the range of values for each feature. From left to right: 4 blue petals, orange circle center, 1 sepal; 6 green petals, purple triangle center, 2 sepals; and 8 yellow petals, blue square center, 3 sepals. See more De Brigard et al. (2017) for further details.

Procedure Procedure followed Experiment 4 of De Brigard et al. (2017), with a few modifications. This paradigm includes three phases: learning, study, and test. Participants began the experiment by reading an instruction screen for a minimum of 30 seconds which detailed the five stimulus features and the possible values those features could take. This instruction screen also displayed two example stimuli for illustration. Participants were instructed that they would see flowers on the screen, one at a time, and were asked to determine whether each flower belonged to the species *avlonia*. Participants were told that *avlonias* differed from other flowers in one simple way (e.g., only *avlonias* have four petals), but that they must discover what makes *avlonia* flowers unique. Participants were told that they must initially guess, but that they would eventually learn what makes a flower an *avlonia*. Crucially, the feature and value that constituted this Learned category (*avlonia*) was counterbalanced across participants. Participants were also assigned a Not-Learned category, constituted by a value of a different feature, of which they were unaware. The Not-Learned category was never mentioned to the participants, statistically independent of the Learned category, and counterbalanced across participants. During each of the three phases of the experiment, each value of each feature was displayed in 1/3

of the trials for that phase, so that the co-occurrence of all feature/value combinations was uniform. Accordingly, 1/3 of all flowers presented were members of the Learned category.

In addition to category conditions, we introduced two further between-subjects manipulations on learning: whether or not the participant was explicitly instructed of the the learned category's discriminating feature and value (instructed vs. not-instructed), and whether the participant actively categorized flowers during learning, or merely watched the screen categorize the flowers as *avlonias* or not-*avlonias* (practiced vs. not-practiced).

Participants learned to categorize flowers into the species *avlonia*. For the practiced condition, participants completed 72 self-paced trials in which they pressed the “y” key if the flower was an *avlonia*, or the “n” key otherwise. Immediate feedback (“Correct” or “Incorrect”) was presented after each key-press for 1s. For the not-practiced condition, participants passively viewed 72 trials in which a flower was shown for 3s, and a categorization (“Avlonia” or “Not Avlonia”) was presented immediately after for 1s. Of the 72 flowers presented, 16 flowers were in the learned category but not the not-learned category, 16 flowers were in the not-learned category but not the learned category, 8 flowers were in both categories, and 32 flowers were in neither category.

In the study phase, participants were asked to memorize 18 flowers. Participants read instructions for this phase for a minimum of 30s. Each flower was shown for 5s following a 1s inter-trial interval. None of these flowers were shown previously in the learning phase. Of these 18 flowers, 4 flowers were in the learned category but not the not-learned category, 4 flowers were in the not-learned category but not the learned category, 2 flowers were in both categories, and 8 flowers were in neither category. Participants were told that they would receive a bonus if they could remember a high number of flowers (XX participants were in fact given a \$X.XX bonus for a hit rate exceeding 85%).

Finally, in the test phase, participants were told that they would see 54 flowers, one by one, and asked to press the “y” key if the flower was old (presented during the study phase), or to press the “n” key otherwise. Participants also read instructions for this phase for a minimum of 30s. Each trial was self-paced with a 1s inter-trial interval. Of these 54 flowers, 18 were presented during study. Of the remaining 36 flowers (lures), 8 flowers were in the learned category but not the not-learned category (learned lures), 8 flowers were in the not-learned category but not the learned category (not-learned lures), 4 flowers were in both categories (both lures), and 16 flowers were in neither category (neither lures). None of the lures appeared in the learning or study phases.

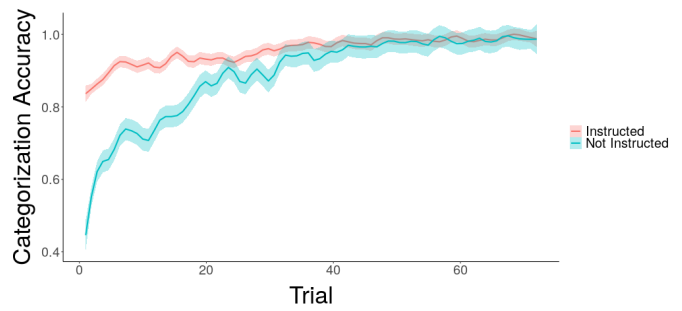


Fig. 2 Learning curves for participants in the practiced condition.

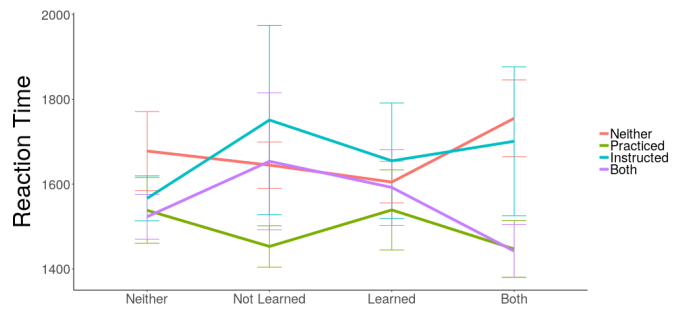


Fig. 3 Reaction Time by category and group. Error bars reflect 95% confidence intervals.

Results

Learning Phase Because the not-practiced group did not make any responses during learning, we limit analysis of this phase to participants in the practiced group. As found in De Brigard et al. (2017), participants in the not-instructed condition started at near chance (65.8%) categorization accuracy in the first 10 trials, and gradually rose to 98.7% accuracy in the last 10 trials. In contrast, participants in the instructed condition began at 89.3% accuracy, and gradually rose to 99.1% accuracy. This confirms that explicit instruction allowed participants to successfully learn the *avlonia* category before practice, although participants could learn the category without explicit instruction.

Test Phase

As outcome variables during the testing phase, we measured reaction time (RT), hits, false alarms (FAs). We also computed individual measures of sensitivity (d') and bias (C) using signal detection theory. To examine the effects of the Learned category, the Not-Learned category, Practice, and Instruction on these variables, we employed 2 (Learned: yes vs. no) \times 2 (Not-Learned: yes vs. no) \times 2 (Practiced: yes vs. no) \times 2 (Instructed: yes vs. no) mixed-effect models with random intercepts for each subject. For hits and FAs, we employed logistic mixed effect models of the same structure using the logit link function.

For RT, we found a significant interaction between Instructed and Not-Learned, $t(37830) = 2.253$, $p = .02$. **Post-**

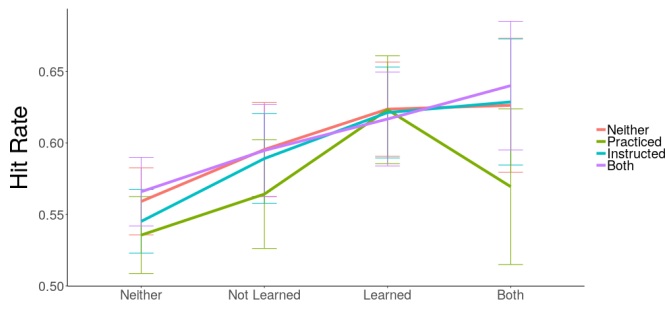


Fig. 4 Hit rates by category and group. Error bars reflect 95% confidence intervals.

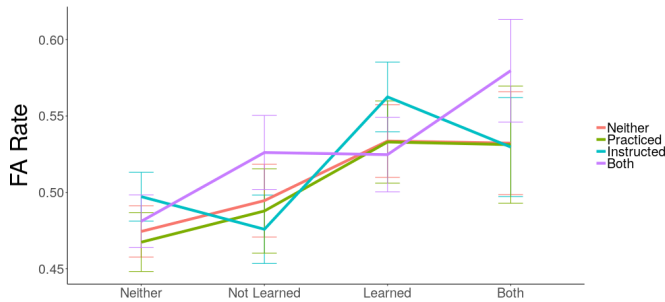


Fig. 5 False alarm rates by category and group. Error bars reflect 95% confidence intervals.

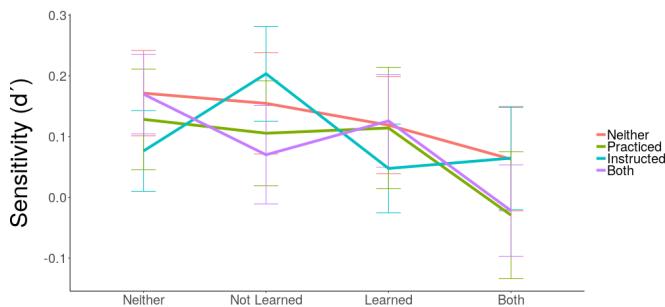


Fig. 6 Sensitivity by category and group. Error bars reflect 95% confidence intervals.

hoc tests? Additionally, there was a near-significant interaction between Instructed and Learned, $t(37830) = 1.672$, $p = .09$, and a near-significant three-way interaction between Instructed, Learned, and Not-Learned, $t(37830) = -1.923$, $p = .054$. **Post-hoc tests?**

Looking at hits, we found a significant main effect of Learned, $z = 3.03$, $OR = 1.34$, $p = .002$. Additionally, there was a near-significant main effect of Not-Learned, $z = 1.70$, $OR = 1.18$, $p = .09$. For FAs, we again found a significant main effect of Learned, $z = 3.92$, $OR = 1.30$, $p < .001$. There was also a significant interaction between Not-Learned and Instructed, $z = -1.99$, $OR = 0.83$, $p = .04$, and a significant three-way interaction between Not-Learned, Instructed, and Practiced, $z = 2.13$, $OR = 1.34$, $p = .03$. **Post-hoc tests?**

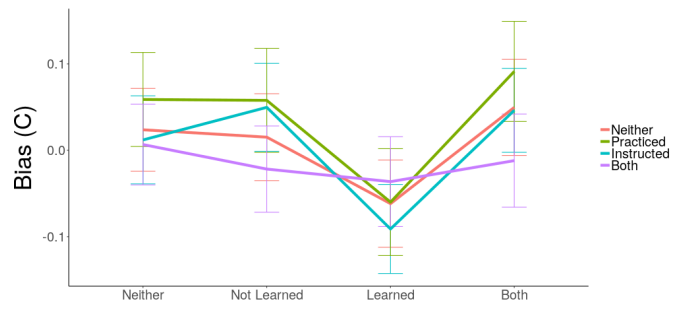


Fig. 7 Response bias by category and group. Error bars reflect 95% confidence intervals.

Looking at sensitivity (d'), we found no significant effects in the mixed-effects model with regard to any of our manipulations. Finally, with respect to response bias (C), we observed a significant main effect of Learned, $t(2130) = -2.00$, $p = .046$, and a significant interaction between Learned and Not-Learned, $t(2130) = 1.98$, $p = .048$. **Post-hoc tests?**

Discussion

In this study we aimed to discover how different forms of learning impact schema formation and deployment. To do so, we tested participant's memory after learning simple rule-based categories under different learning constraints (practice only, instruction only, both, neither). Largely, we found little behavioral difference between these groups, suggesting that they may be equally effective with regard to forming lasting schemas. However, we did find that the Learned category had a significant impact on hits, FAs, and response bias (C), supporting the idea that all of these forms of category learning produce representations that are synonymous with schemas (**CITE**).

Future work in this area could reveal boundary conditions in which the representations produced under these different learning constraints are dissociable. There is good reason to suspect that such boundary conditions will exist—under the recent perspective that category learning recruits multiple memory systems depending on the category's nature and the circumstances of learning, we would expect that practice with immediate feedback would produce more striatal learning, whereas explicit instruction would result in rule-based learning in the hippocampus and prefrontal cortex Ashby and Maddox (2011). We would then predict a corresponding double-dissociation between category learning impairment in Parkinson's patients and medial temporal lobe amnesiacs. Because this paradigm allows for testing the memory effects of newly-learned categories independently of the perceptual or statistical features of the stimuli, we believe that it would be fertile ground for testing this hypothesis in fMRI.

Acknowledgements**References**

- Ashby FG, Maddox WT (2011) Human category learning 2.0. *Annals of the New York Academy of Sciences* 1224(1):147–161
- De Brigard F, Brady TF, Ruzic L, Schacter DL (2017) Tracking the emergence of memories: A category-learning paradigm to explore schema-driven recognition. *Memory & cognition* 45 1:105–120