

Effects of Category Learning Strategies on Recognition Memory

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Abstract

Recent evidence has demonstrated similar effects of schematic and categorical knowledge on recognition memory, suggesting strong parallels between these kinds of knowledge. However, while it has been shown that differences in category learning strategies impact classification accuracy, it is unknown whether they also have downstream effects on subsequent recognition memory. The present study sought to investigate the effect of two category learning strategies—learning (1) with or without explicit instruction, and (2) with or without supervision—on subsequent recognition memory. Our findings suggest that learned categories had schema-like effects on recognition memory regardless of the particular strategy employed in initially learning these categories. These results suggest that rule-based category learning, regardless of the learning strategy, may be tantamount to schema acquisition.

Keywords: Category Learning; Recognition Memory; Supervised Learning; Schema.

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Much research on episodic memory has shown that previously acquired knowledge structures—or *schemas*—affect recognition (Bartlett, 1932; Posner & Keele, 1968). For example, participants are more likely to remember schema-inconsistent relative to schema-consistent targets from passages, like an abnormal event in an otherwise typical story about going to the doctor (Bower, Black & Turner, 1979). Likewise, in recognition tests, people are more likely to false alarm to schema-consistent relative to schema-inconsistent lures, like falsely reporting having seen a stethoscope in a doctor's office, even when there wasn't one (Brewer & Treyens, 1981; Lampinen, Copeland, & Neuschatz, 2001). Because schema-acquisition takes time, and schemas can be quite complex (e.g., we all have a vast amount of knowledge about what occurs or doesn't occur at doctor's offices, Bower et al. 1979), learning and expertise about particular schemas tends to vary among participants. Thus, research on schematic influences on recognition memory typically involves one of two experimental strategies: either within-subject designs to evaluate effects of pre-acquired schemas on different recognition tests (Graesser & Nakamura, 1982; Roediger & McDermott, 1995), or between-subject designs where participants with different expertise face identical recognition tests (Castel et al., 2007). Unfortunately, neither of these strategies directly manipulates schema-acquisition to evaluate its effects on recognition memory.

However, accumulating evidence shows strong connections between effects of schematic and categorical knowledge on recognition memory (Sakamoto, 2012). For example, Palmieri and Nosofsky (1995) instructed participants to learn to categorize stimuli according to an imperfect rule. Despite such categories being much simpler than complex schemas, and despite having been acquired in the same session, they found analogous results to those found in the schema literature, as participants were more likely to remember rule-inconsistent items relative to rule-consistent items on a subsequent memory test. Recently, Sakamoto and Love (2004) manipulated the strength

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of the category rule by varying the number of rule-consistent and rule-inconsistent items. Consistent with findings on schemas and recognition memory (Rojahn & Pettigrew, 1992), Sakamoto and Love found that when the rule was stronger (i.e., included fewer rule-inconsistent items during learning), exceptions were remembered better than when the rule was weaker. Such results bolster the claim that acquiring a schema is tantamount to learning a category (Love, 2013), at least in regards to their effects on subsequent memory.

Building upon these parallels, De Brigard and colleagues (2017) developed a paradigm to explore how learning a novel category influences subsequent memory for items that belonged to the learned category, relative to items that belonged to a different not-learned category or to no category at all. They showed that learning a category increases both hits and false alarms for category-consistent stimuli, broadly consistent with the schema literature (e.g., Lampinen et al. 2001). More recently, employing a version of the same paradigm, Yin et al (2019) replicated these findings, but also showed that participants that successfully learned the category showed better old-new discrimination in a recognition test, relative to those who failed to learn the category, suggesting learned categories enhanced memory performance.

But a question remains as to whether different learning strategies influence subsequent recognition memory above and beyond the fact that a category is learned. Previous research on category learning has focused on differences in classification accuracy as a function of learning strategy. For instance, Allen and Brooks (1991) found advantages in classification accuracy and speed when the category was learned without explicit instruction relative to when the rule was explicitly revealed. Other studies have explored differences between supervised versus unsupervised learning. Love (2002), for instance, found an advantage for linear over non-linear category structures during incidental unsupervised learning, whereas no such advantage was

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evident when the category was learned with feedback. Now, provided that a category is well-learned, it is worth wondering whether or not the *manner* in which the category was learned impacts memory subsequently. The current study explores this question by modifying De Brigard et al.'s (2017) paradigm to investigate the effects of four category learning strategies on recognition memory: 1) learning with and without explicit instruction, and 2) learning with and without supervised practice.

Method

Participants

To match the statistical power obtained in De Brigard et al. (2017) in each between-subjects condition, 867 participants were recruited via Amazon Mechanical Turk (<https://www.mturk.com>). All participants were from the US, had at least 100 approved HITs, had an overall HIT approval rate of at least 95%, and received \$2.00 in compensation. As we were interested in how successfully learned categories impact memory performance, data from 134 participants were excluded because of failure to learn the category above 85% accuracy during the last 20 trials of learning, as in De Brigard et al. (2017), leaving 733 participants (151 Practiced only, 208 Instructed only, 184 Both, 190 Neither) for data analysis. Out of 39,582 test phase trials across all participants, 188 trials with response time greater than 3 standard deviations (SDs) from the mean (i.e., above 15.16 seconds) were also discarded. All participants provided informed consent in accordance with Duke University IRB.

Materials

Stimuli consisted of MATLAB (2018b)-generated flowers, used previously in De Brigard et al. (2017). These flowers varied over five features (i.e., petal number, petal color, center shape,

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center color, and sepal number), with each feature taking three possible values (Figure 1A). Flowers were displayed on the center of an otherwise white screen.

Procedure

The procedure, which closely followed Experiment 4 of De Brigard et al. (2017), included three phases: learning, study, and test. The experiment began with an instruction screen (~30s) detailing the five stimulus features and their possible values, with two example stimuli displayed for illustration. Participants were instructed that they would see flowers on the screen, one at a time, and would be asked to determine whether each flower belonged to the species *avlonia*. The feature and value that constituted this Learned category (*avlonia*) was counterbalanced across participants. To isolate effects of the Learned category from possible effects of non-conceptual stimulus features, participants were also assigned a Not-Learned category, randomly defined by a value of a different feature, of which they were unaware. The Not-Learned category was never mentioned to the participants, was statistically independent of the Learned category, and was counterbalanced across participants, serving only as a baseline for analysis. 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.

Additionally, we introduced two counterbalanced between-subjects manipulations on learning: whether the participant was explicitly instructed of the Learned category's rule (Instruction: Instructed, Not-Instructed), and whether the participant actively categorized flowers during learning, or merely watched as flowers were categorized on the screen (Practice: Practiced, Not-Practiced). Specifically, in the Instructed condition, participants were told how to identify *avlonias*, (e.g. "*Avlonias* are flowers with six petals"). In the Not-Instructed condition, participants

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were told only that they would have to learn what feature and value defined the species *avlonia*. In 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”/“Incorrect”) was presented after each key-press for 1s. In the Not-Practiced condition, participants instead passively viewed 72 trials in which a flower was shown for 3s, and a categorization (“Avlonia”/“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 read instructions (for a minimum of 30s) in which they were asked to memorize 18 flowers. Each flower was shown for 5s after a 1s inter-trial interval. None of these flowers were shown previously. Of these 18 flowers, 4 were in the Learned category but not the Not-Learned category, 4 were in the Not-Learned category but not the Learned category, 2 were in Both categories, and 8 were in Neither category. Participants were told that they would receive a bonus if they could remember a high number (85%) of flowers.

Finally, in the test phase, participants read instructions (for a minimum of 30s), in which they were told that they would see 54 flowers, one by one, and asked to press the “y” if the flower was old, or “n” otherwise. 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 were in the Learned category but not the Not-Learned category, 8 were in the Not-Learned category but not the Learned category, 4 were in Both categories, and 16 were in Neither category. None of the lures appeared in the learning or study phases.

Results

Learning Phase. Because the participants in the Not-Practiced condition did not make responses during learning, we report results from those in the Practiced condition only. As found in De Brigard et al. (2017), participants in the Not-Instructed condition started at near chance ($M = 65.4\%$, $SD = 20.2\%$) categorization accuracy in the first 10 trials, and gradually rose to near ceiling ($M = 98.7\%$, $SD = 3.8\%$) accuracy in the last 10 trials. In contrast, participants in the Instructed condition began with high ($M = 89.2\%$, $SD = 17.4\%$) accuracy, and quickly rose to near ceiling ($M = 99.1\%$, $SD = 3.1\%$) accuracy (Figure 1B). These results confirm that, after excluding for participants with learning accuracy below 85% in the last 20 trials, all participants successfully learned the category of interest.

Test Phase. As outcome variables during the testing phase, we measured reaction time (RT), hits, and false alarms (FAs), as well as hierarchical estimates of sensitivity (d') and bias (C). For all outcome variables, unless otherwise noted, we fit Bayesian mixed-effects models in R using the *brms* package with 5 chains, 1000 iterations of burn-in, and 1500 iterations of sampling (Bürkner, 2017). In accordance with Bayesian parameter estimation, for each effect, we report posterior medians, 95% Highest Density Intervals (*HDI*s), probability of direction (*pd*), and percentage of the 95% *HDI*s inside a Region of Practical Equivalence (ROPE). Similar to a p -value, probability of direction is the proportion of posterior samples greater than (or less than) 0 and is a metric of effect existence, where $pd > 97.5\%$ is suggestive of an effect at $\alpha = .05$ (Makowski, Ben-Shachar, Chen, & Lüdtke, 2019). In contrast, the percentage of the 95% *HDI* inside a ROPE is a metric of effect significance that counts the proportion of posterior samples inside a null region (Kruschke, 2011). While avoiding black-and-white thinking, we use $< 5\%$ and $> 95\%$ as rough benchmarks for rejecting and accepting the null, respectively.

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Hit rate and false alarm rate separately. For hits and FAs, we used 2 (Learned Category) x 2 (Not-Learned Category) x 2 (Practiced) x 2 (Instructed) Bayesian mixed-effect models with random intercepts for each subject, uncorrelated random slopes for Learned Category and Not-Learned Category, and Bernoulli distributions with a logit link. We used weakly informative Gaussian priors on all coefficients, with means of 0 and standard deviations of 4, and a ROPE width of 0.15. We found that flowers in the Learned category ($Mdn = 0.65$, $HDI = [0.60, 0.70]$) were recognized more frequently than flowers not in the Learned category ($Mdn = 0.57$, $HDI = [0.54, 0.61]$), $\beta = .32$, $HDI = [.1, .54]$, $pd = 99.9\%$, 3.9% in ROPE. In contrast, there was evidence against effects of Not-Learned Categories on recognition memory, $\beta = .18$, $HDI = [-.03, .39]$, $pd = 95\%$, 40.2% in ROPE, whether participants were allowed to practice during categorization, $\beta = -.08$, $HDI = [-.29, .13]$, $pd = .75.9\%$, 76% in ROPE, and whether they were given explicit instructions about the category, $\beta = -.08$, $HDI = [-.27, .12]$, $pd = 77.9\%$, 78.9% in ROPE. There was also evidence against all 2, 3, and 4-way interactions between these variables (all $pds < 87.5\%$, $> 22.6\%$ in ROPE).

For FAs, we again found weak evidence that lures in the Learned category ($Mdn = 0.53$, $HDI = [0.48, 0.57]$) were more likely to be falsely recognized than lures not in the Learned category ($Mdn = 0.46$, $HDI = [0.43, 0.50]$), $\beta = .26$, $HDI = [.08, .43]$, $pd = 99.8\%$, 9.2% in ROPE. Conversely, there was evidence against an effect of Not-Learned Category, $\beta = .08$, $HDI = [-.07, .23]$, $pd = 86.4\%$, 81.7% in ROPE, whether participants were allowed to practice categorization, $\beta = -.03$, $HDI = [-.23, .17]$, $pd = 62.3\%$, 88.5% in ROPE, and whether they were given explicit instructions about the category, $\beta = .11$, $HDI = [-.07, .29]$, $pd = .87.9\%$, 67.0% in ROPE. There was moderate to strong evidence against all other 2, 3, and 4-way interactions between these

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variables (all $pds < 97.7\%$, $> 15\%$ in ROPE). Posterior medians and 95% HDI s for hits and FAs are presented in Table 1 (for further results, see SI).

Discriminability (d') and response bias (C). Next, hierarchical estimates of SDT parameters (d' , C) were calculated using a 2 (Learned Category) x 2 (Not-Learned Category) x 2 (Practiced) x 2 (Instructed) x 2 (Old) Bayesian mixed-effect model with random intercepts for each subject, uncorrelated random slopes for Learned Category, Not-Learned Category, and Old/New status, and a Bernoulli distribution with a probit link. We used weakly informative Gaussian priors on all coefficients, with means of 0 and standard deviations of 2, and a ROPE range of 0.075. In this model, the intercept represents estimates of $-C$, the effect of Old represents estimates of d' , effects of our factors represent effects on C , and interactions with Old represent effects on d' (DeCarlo, 1998). There was strong evidence for a main effect of Old/New status, suggesting that subjects had positive estimates of d' , $\beta = 0.27$, $HDI = [0.18, 0.36]$, $pd = 100\%$, 0% in ROPE. For response bias (C), there was evidence for an effect of Learned Category, $\beta = .16$, $HDI = [.05, .26]$, $pd = 99.8\%$, 3.8% in ROPE, suggesting that participants were more likely to respond 'Old' for flowers in the Learned category ($Mdn = 0.53$, $HDI = [0.49, 0.57]$) compared to flowers not in the Learned category ($Mdn = 0.47$, $HDI = [0.44, 0.50]$). Conversely, there was evidence against effects of practice during the categorization phase, $\beta = -.02$, $HDI = [-.14, .09]$, $pd = 65.3\%$, 80.9% in ROPE, explicit instructions about the category, $\beta = .07$, 95% $HDI = [-.04, .17]$, $pd = 89.2\%$, 57.5% in ROPE, and Not-Learned category status, $\beta = .05$, $HDI = [-.04, .14]$, $pd = 86.4\%$, 70.7% in ROPE on response bias. There was also evidence against such effects on d' : practice status, $\beta = -.03$, $HDI = [-.17, .11]$, $pd = 65.7\%$, 70.4% in ROPE, explicit instruction status, $\beta = -.11$, $HDI = [-.24, .01]$, $pd = 95.6\%$, 27.6% in ROPE, Learned category status, $\beta = .04$, $HDI = [-.11, .19]$, $pd = 69.2\%$, 66.6% in ROPE, and Not-Learned category status, $\beta = .06$, $HDI = [-.09, .20]$, $pd = 77.8\%$, 59.0%

in ROPE. Finally, there was evidence against all interactions between Learned category status, Not-Learned category status, Practice, Instruction, and Old (all $pds < 97.3\%$, $> 11.2\%$ in ROPE). Posterior medians and 95% HDIs of estimates of d' and C are presented in Table 1.

Reaction time. To examine effects on RT, we employed 2 (Learned Category: Yes, No) x 2 (Not-Learned Category: Yes, No) x 2 (Practiced: Yes, No) x 2 (Instructed: Yes, No) x 2 (Old: Yes, No) Bayesian mixed-effect model with random intercepts for each subject, uncorrelated random slopes for Learned Category, Not-Learned Category, and Old, predicting the parameters μ (identity link) and τ (right-skewness, log link) of an Ex-Gaussian distribution, keeping σ fixed at the population-level. The Ex-Gaussian distribution is commonly used to model reaction time distributions by separately accounting for the mean (μ) and skewness (τ), thereby reducing the effect of outliers on the mean in such positively skewed distributions (Balota & Yap 2011). We used weakly informative Gaussian priors on all coefficients, with means of 0 and standard deviations of 2.5 for μ , and with means of 0 and standard deviations of 1 for τ , and a ROPE width of $[-.157, .157]$, which represents a standardized effect of 0.1. To aid convergence, we used 3000 sampling iterations with a thinning rate of 3. Posterior medians and 95% HDIs on reaction times are reported in Table 2 (for further results, see SI). We found evidence against significant effects and interactions of all factors on μ ($pd < 0.927$, $> 76\%$ within ROPE). While there was evidence for the existence of effects of some factors on τ ($pd < 0.99$), these effects were so small as to be either uncertain or negligible ($> 29.1\%$ within ROPE). These results suggest that any differences in RT arising from our manipulations were negligible.

Discussion

Recent evidence has demonstrated strong connections between schematic and categorical knowledge in terms of their effects on recognition memory (Sakamoto and Love, 2012).

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Additionally, in the category learning literature, several findings have shown differences in classification accuracy as a function of category learning strategy. However, the downstream effects on recognition memory of different category learning strategies are less clear. The present study employed a variation on a novel paradigm (De Brigard et al, 2017) to investigate whether practice and instruction during category learning had downstream effects on recognition memory.

The current study yielded two main findings. First, it replicated prior results using the same paradigm (De Brigard et al, 2017; Yin et al., 2019). Specifically, we found that learning a category yielded an increase in hits and false alarms for stimuli in the learned category compared to stimuli not in the learned category. Additionally, we replicated previous findings showing a decrease in bias (i.e., C) for items of the learned category relative to items not in the learned category. We take this replication to, once again, contribute to the extant literature showing that such rule-based category learning is akin to schema acquisition, and that the cognitive processes by means of which we acquire new schemas have much in common with those deployed in the acquisition of new categories (Sakamoto and Love, 2004; Sakamoto and Love, 2017).

The second finding pertains to our manipulations of practice and instruction. Our analyses suggested evidence against substantial differences in memory accuracy and response time between the four conditions (i.e., instructed/practiced, instructed/not-practiced, not-instructed/practiced, not-instructed/not-practiced), suggesting that different learning strategies may be equally effective in forming schema-like representations. More precisely, our results suggest that neither being instructed explicitly of the category-inclusion rule, nor practicing category classification during learning, has any differential downstream effect on recognition. These results show that while category learning strategies may have consequences for immediate classification accuracy, they do not differentially affect subsequent recognition memory, suggesting that these different learning

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strategies are equally successful in generating the categorical/schematic knowledge structure that brings about the reported increase for hit and false alarms for schema-consistent items.

Future work could build on these findings by utilizing ROC curves to obtain more reliable and precise measures of recognition differences between the conditions (Wixted, 2007). Likewise, as d' was relatively low (<0.5) in all conditions, such memory differences might arise when memory accuracy overall is increased. Finally, although we have observed little difference in recognition memory between categories learned with and without explicit instruction and with and without supervised practice, further research may reveal interesting differences in the neural representations of these categories associated with learning strategies. For instance, supervised learning may form a reinforcement-based representation in the striatum, similar to representations of information-integration categories, whereas unsupervised learning may create more schema-like representations in the hippocampus and vmPFC (Ashby & Maddox, 2005). 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 such hypotheses in fMRI.

Open Practices Statement

The data, analysis code, and materials for all experiments are available on the Open Science Framework at <https://osf.io/mbrfc/> and this experiment was not preregistered.

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Figure 1

A



B

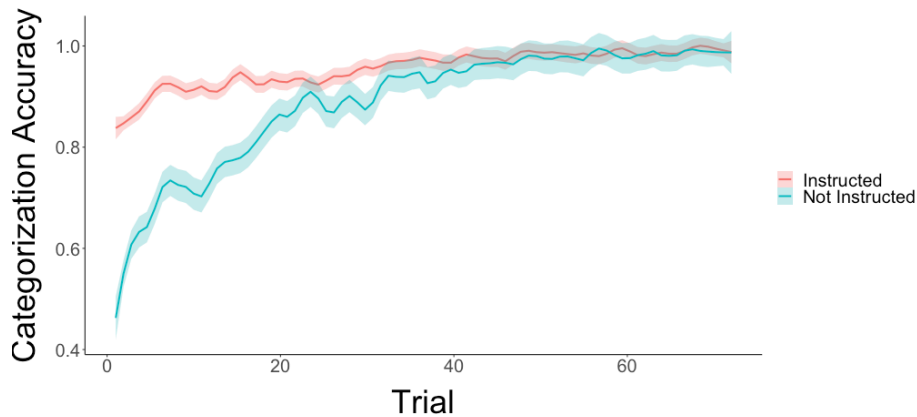


Figure 1: A. Examples of Stimuli. Stimuli consisted of flowers varying across five dimensions, which each dimension taking on of three possible values: number of petals (four, six, or eight), petal color (blue, green or yellow), center shape (circle, triangle, or square), center color (orange, purple, or turquoise), and number of sepals (one, two, or three). Figure 1A depicts all possible values of the five features. **B. Learning performance.** Mean categorization performance for the Practiced + Instructed and Practiced + Not-Instructed conditions. Error bars represent standard errors from the mean.

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P	I	L	NL	Hits	FAs	d'	C
0	0	0	0	0.57 [0.54, 0.61]	0.46 [0.43, 0.50]	0.27 [0.18, 0.36]	0.08 [0.01, 0.16]
0	0	0	1	0.61 [0.57, 0.66]	0.48 [0.44, 0.53]	0.33 [0.20, 0.46]	0.03 [-0.06, 0.13]
0	0	1	0	0.65 [0.60, 0.70]	0.53 [0.48, 0.57]	0.31 [0.17, 0.43]	-0.07 [-0.18, 0.04]
0	0	1	1	0.66 [0.59, 0.72]	0.53 [0.47, 0.59]	0.33 [0.13, 0.52]	-0.07 [-0.21, 0.07]
0	1	0	0	0.55 [0.52, 0.58]	0.49 [0.46, 0.52]	0.16 [0.07, 0.25]	0.02 [-0.05, 0.09]
0	1	0	1	0.61 [0.56, 0.65]	0.47 [0.43, 0.50]	0.36 [0.23, 0.49]	0.08 [-0.02, 0.17]
0	1	1	0	0.64 [0.59, 0.69]	0.57 [0.52, 0.61]	0.20 [0.08, 0.32]	-0.17 [-0.28, -0.06]
0	1	1	1	0.66 [0.60, 0.73]	0.53 [0.48, 0.59]	0.34 [0.16, 0.53]	-0.09 [-0.22, 0.05]
1	0	0	0	0.55 [0.51, 0.59]	0.46 [0.42, 0.49]	0.24 [0.14, 0.35]	0.11 [0.02, 0.19]
1	0	0	1	0.58 [0.52, 0.63]	0.48 [0.43, 0.53]	0.25 [0.11, 0.40]	0.05 [-0.06, 0.16]
1	0	1	0	0.65 [0.60, 0.70]	0.53 [0.48, 0.58]	0.31 [0.16, 0.45]	-0.08 [-0.20, 0.05]
1	0	1	1	0.61 [0.52, 0.68]	0.52 [0.45, 0.59]	0.20 [-0.03, 0.40]	-0.05 [-0.22, 0.10]
1	1	0	0	0.58 [0.54, 0.61]	0.48 [0.44, 0.51]	0.25 [0.15, 0.34]	0.06 [-0.02, 0.13]
1	1	0	1	0.62 [0.57, 0.66]	0.53 [0.48, 0.57]	0.23 [0.09, 0.36]	-0.07 [-0.17, 0.02]
1	1	1	0	0.64 [0.59, 0.69]	0.53 [0.48, 0.57]	0.29 [0.16, 0.42]	-0.07 [-0.18, 0.04]
1	1	1	1	0.68 [0.61, 0.75]	0.60 [0.54, 0.65]	0.25 [0.04, 0.44]	-0.23 [-0.38, -0.09]

Table 1: Median posterior estimates and 95% HDIs of hits, FAs, sensitivity (d'), and bias (C). **P** = Practiced; **I** = Instructed; **L** = Learned Category; **NL** = Not-Learned Category.

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Old	P	I	L	NL	RT (s)
0	0	0	0	0	1.68 [1.54, 1.82]
0	0	0	0	1	1.67 [1.53, 1.82]
0	0	0	1	0	1.69 [1.55, 1.84]
0	0	0	1	1	1.71 [1.57, 1.86]
0	0	1	0	0	1.58 [1.44, 1.72]
0	0	1	0	1	1.59 [1.45, 1.73]
0	0	1	1	0	1.58 [1.44, 1.72]
0	0	1	1	1	1.58 [1.44, 1.72]
0	1	0	0	0	1.59 [1.43, 1.76]
0	1	0	0	1	1.61 [1.45, 1.78]
0	1	0	1	0	1.59 [1.43, 1.75]
0	1	0	1	1	1.60 [1.45, 1.78]
0	1	1	0	0	1.51 [1.37, 1.64]
0	1	1	0	1	1.50 [1.37, 1.64]
0	1	1	1	0	1.52 [1.37, 1.65]
0	1	1	1	1	1.49 [1.35, 1.63]
1	0	0	0	0	1.69 [1.55, 1.83]
1	0	0	0	1	1.66 [1.51, 1.81]
1	0	0	1	0	1.69 [1.54, 1.84]
1	0	0	1	1	1.69 [1.55, 1.85]
1	0	1	0	0	1.58 [1.45, 1.73]
1	0	1	0	1	1.58 [1.43, 1.71]
1	0	1	1	0	1.57 [1.43, 1.71]
1	0	1	1	1	1.56 [1.42, 1.70]
1	1	0	0	0	1.59 [1.43, 1.76]
1	1	0	0	1	1.58 [1.42, 1.75]
1	1	0	1	0	1.58 [1.42, 1.75]
1	1	0	1	1	1.59 [1.41, 1.75]
1	1	1	0	0	1.49 [1.36, 1.63]
1	1	1	0	1	1.49 [1.35, 1.63]
1	1	1	1	0	1.45 [1.32, 1.60]
1	1	1	1	1	1.47 [1.33, 1.61]

Table 2: Median posterior estimates and 95% HDIs of reaction time (in seconds). **P** = Practiced; **I** = Instructed; **L** = Learned Category; **NL** = Not-Learned Category.