Method

Subjects

The subjects were 214 students from Indiana University who participated in partial fulfillment of an undergraduate psychology course requirement. Subjects were randomly assigned to four training conditions. There were 77 subjects in the low-distortion condition, 78 in the medium-distortion condition, 75 in the high-distortion condition and 74 in the mixed-distortion condition. All subjects had normal or corrected-to-normal vision.

Stimuli and apparatus

The stimuli used in this experiment were dot patterns generated using the Posner-Keele (1968) statistical-distortion algorithm. For each individual subject, prototypes for three different categories were generated by placing 9 dots at random grid positions in the central 30 × 30 area of a 50 × 50 grid.

Different training and transfer patterns of each category were generated using the statistical-distortion procedure of Posner et al. (1968). Each pattern was constructed from the prototype of its category by displacing each dot by a random direction and distance in accordance with the Posner et al. procedure. Low-level, medium-level and high-level distortions were generated by moving the individual dots, on average, 4, 6 and 7.7 Posner-levels away from their prototype. Each individual subject was presented with a unique set of randomly generated prototypes and training and transfer patterns.

Procedure

A standard learning-transfer paradigm was used in this experiment. In the learning phase, subjects were trained to classify a set of training patterns into three categories. On each trial, a dot pattern was presented at the center of the computer screen and remained visible until a subject responded with a key press. After the response, corrective feedback appeared for 2s below the presented pattern. A different set of training patterns was presented in each of the 10 training blocks. The learning phase was followed by a transfer phase where subjects classified selected novel patterns as well as a subset of training patterns into the same three categories. No corrective feedback was given on any test trial.

For each individual subject, prototypes for three different categories were randomly generated. Subjects were randomly assigned to one of the four training conditions that differ in terms of the variability of the training patterns. In each condition, 90 training patterns (9 per block) were randomly generated around each of the three category prototypes (270 patterns in total). The category prototypes were distorted by various levels using the Posner-Keele (1968) statistical-distortion algorithm to generate the training patterns for the four training conditions: all low-distortions, all medium-distortions, all high-distortions, and mixture (equal number) of the three distortion levels, respectively. The test patterns consisted of 27 old distortions that were presented in the training phase (9 per category), 3 prototypes (1 per category), 9 new low-level distortions (3 per category), 18 new medium-level distortions (6 per category), 27 new high-level distortions (9 per category). Each pattern was presented once in a random order for each subject for a total of 84 trials.

Results

Learning. Figure 1 shows the average proportion of correct classification responses over the training blocks for each of the four training conditions. Across all the training conditions, the classification accuracy gradually improves over the course of training. The low-distortion training condition shows the highest accuracy, the medium- and mixed-distortion conditions show intermediate levels of accuracy, while the high distortion condition shows the lowest accuracy.

To confirm these observations, we conducted a 4x10 mixed-model ANOVA using training conditions (low, med, high, mixed) and blocks as factors. The analysis revealed a significant main effect of blocks, F(6.35, 1905.07) = 84.44, p < .001, η2 = .220\*. The main effect of training conditions was also significant, F(3,300) = 82.85 , p < .001, η2 = .453, as was the interaction effect between learning condition and blocks, F(19.05, 1905.07) = 2.865, p < .001, η2 = .028. The mean proportion of correct responses for the final training blocks is higher in the low condition (M = 0.905) than in the medium condition (M = 0.695), t(132.3) = 8.05, p < .001\*\*, and higher in the medium condition than in the high condition (M = 0.502), t(151.0) = 6.33, p < .001.

Transfer. Figure 2 shows the mean proportion of correct responses for the different types of test patterns. The general trend is that, across training conditions, the classification accuracy is the highest for the prototypes, and decreases in the order of low-, medium- and high-level distortion test patterns. Moreover, the novel high distortions were classified with notably lower accuracy in the high-distortion training condition than in the three other conditions. In addition, the novel medium distortions were also classified with lower accuracy in the medium-distortion and mixed-distortion training condition than in the low-distortion condition.

To confirm these observations, we conducted a 4x4 mixed-model ANOVA, using condition (low, medium, high, mixed) and novel pattern type (prototype, new-low, new-medium, new-high) as factors. The analysis revealed a significant main effect of pattern type, F(2.62, 779.36) = 128.5, p < .001, η2 = .092; a significant main effect of learning condition, F(3,300) = 15.35, p < .001, η2 = .091; and a significant interaction between the two factors, F(7.79, 779.36) = 4.4, p < .001, η2 = .010. For the novel high-distortion patterns, the mean proportion of correct responses is significantly lower in the high condition (M = .512) than in the medium condition (M = .631), t(150.7) = 4.024, p < .001, the mixed condition (M = .593), t(146.8) = 2.655, p = .036, and the low condition (M = .637), t(135.5) = 4.786, p < .001. For the novel medium-distortion patterns, the mean proportion of correct responses is significantly lower in the medium condition (M = .692) than in the low condition (M = .771), t(146.8) = 2.631, p = .036.

In our subsequent modeling analysis, we decided to conduct separate analyses on all subjects and those subjects with adequate overall accuracy during the transfer phase. As can be seen in Figure 3, there are discernible variations in both the overall classification accuracy and the subject-level distribution across training conditions. For each condition, we computed individual test accuracies by averaging the proportions of correct responses over all pattern types, and decided to retain for our subsequent analyses the proportion of subjects with the highest 90% of individual test accuracies in each condition (rather than setting separate training criterion for each condition). As a result, there remained 70 subjects in the low-distortion condition, 71 in the medium-distortion condition, 68 in the high-distortion condition and 67 in the mixed-distortion condition. Even after removing the lower performing subjects from all conditions, mean proportion correct for novel high-distortion patterns in the high-distortion condition (M = 0.538) remained significantly lower than in the medium-distortion condition (M=0.661), t(135.0)=4.345, p< .001, the mixed-distortion condition (M=0.626), t(132.7) = 3.045, p = .032, and the low-distortion condition (M=0.657),t(119.4) = 4.660, p< .001. For the novel medium-distortion patterns, the mean proportion correct in the medium-distortion condition (M = 0.732) also remained significantly lower than the low-distortion condition (M = .809), t(125.4) = 3.210, p = .008. As shown in Figure 4, the overall patterns of transfer results stayed the same as in the analysis in which all subjects were included.

\* The Greenhouse-Geisser correction was applied for violation of the sphericity assumption.

\*\* The reported p-values have been adjusted using the Bonferroni method to account for multiple comparisons.

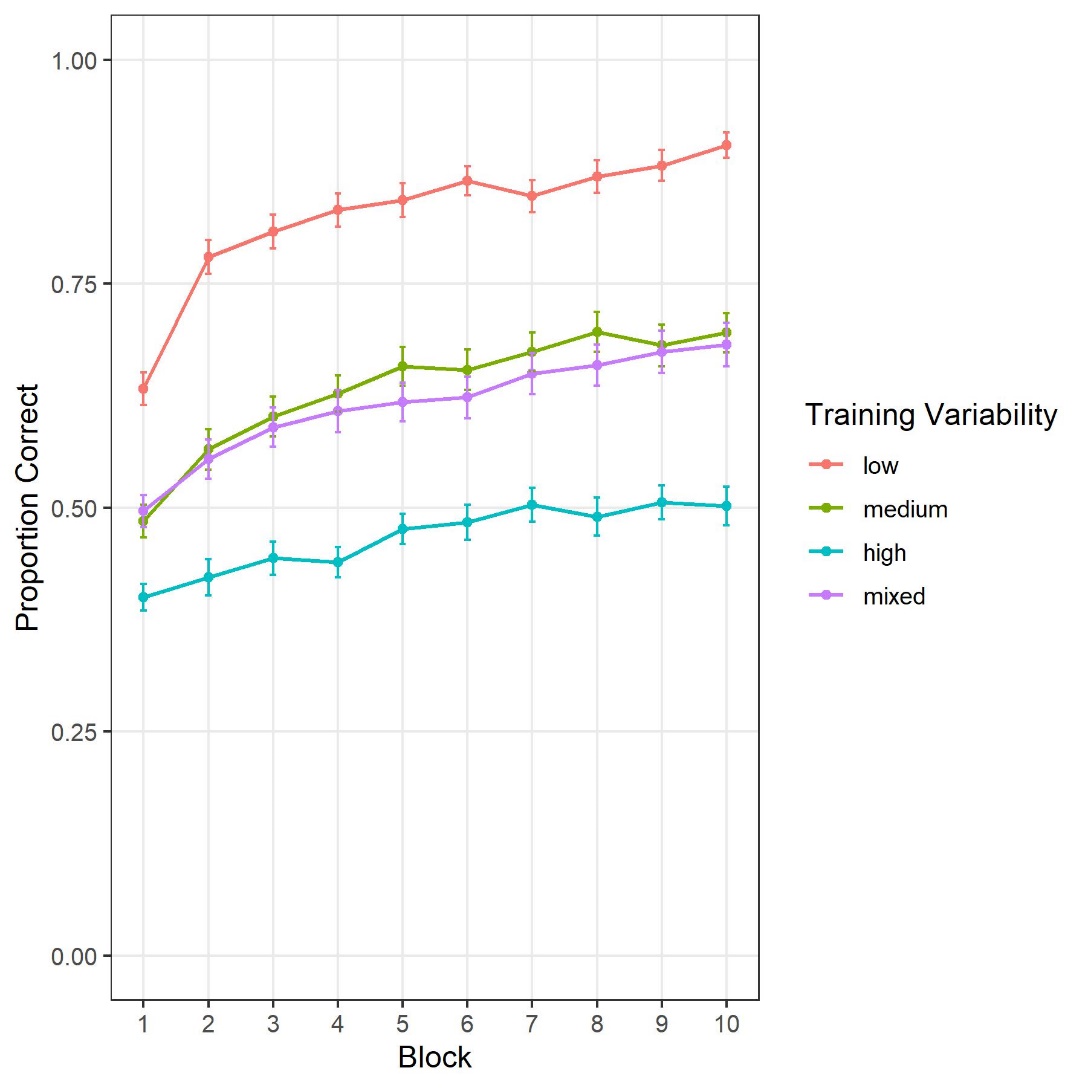


Figure 1

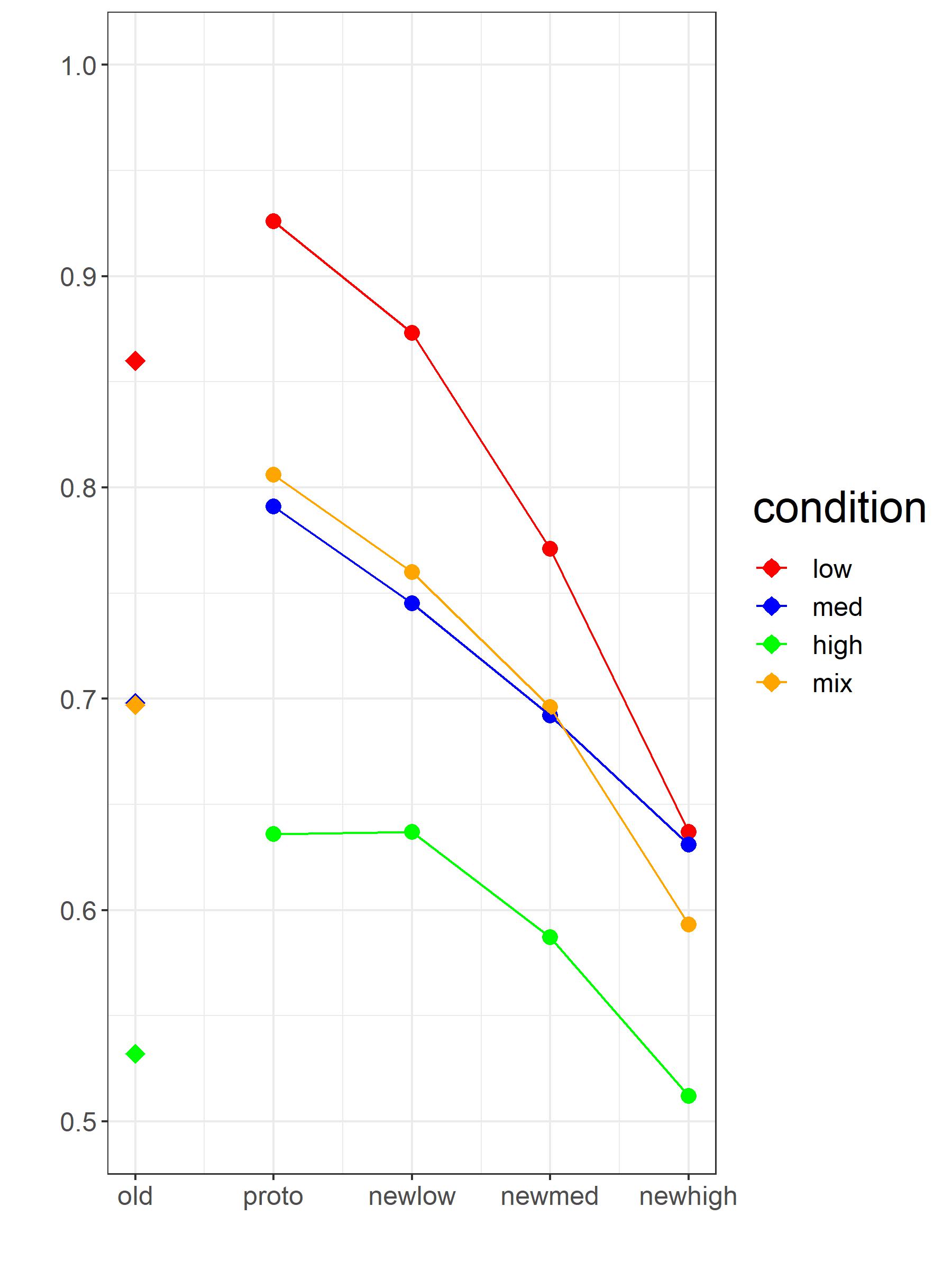


Figure 2

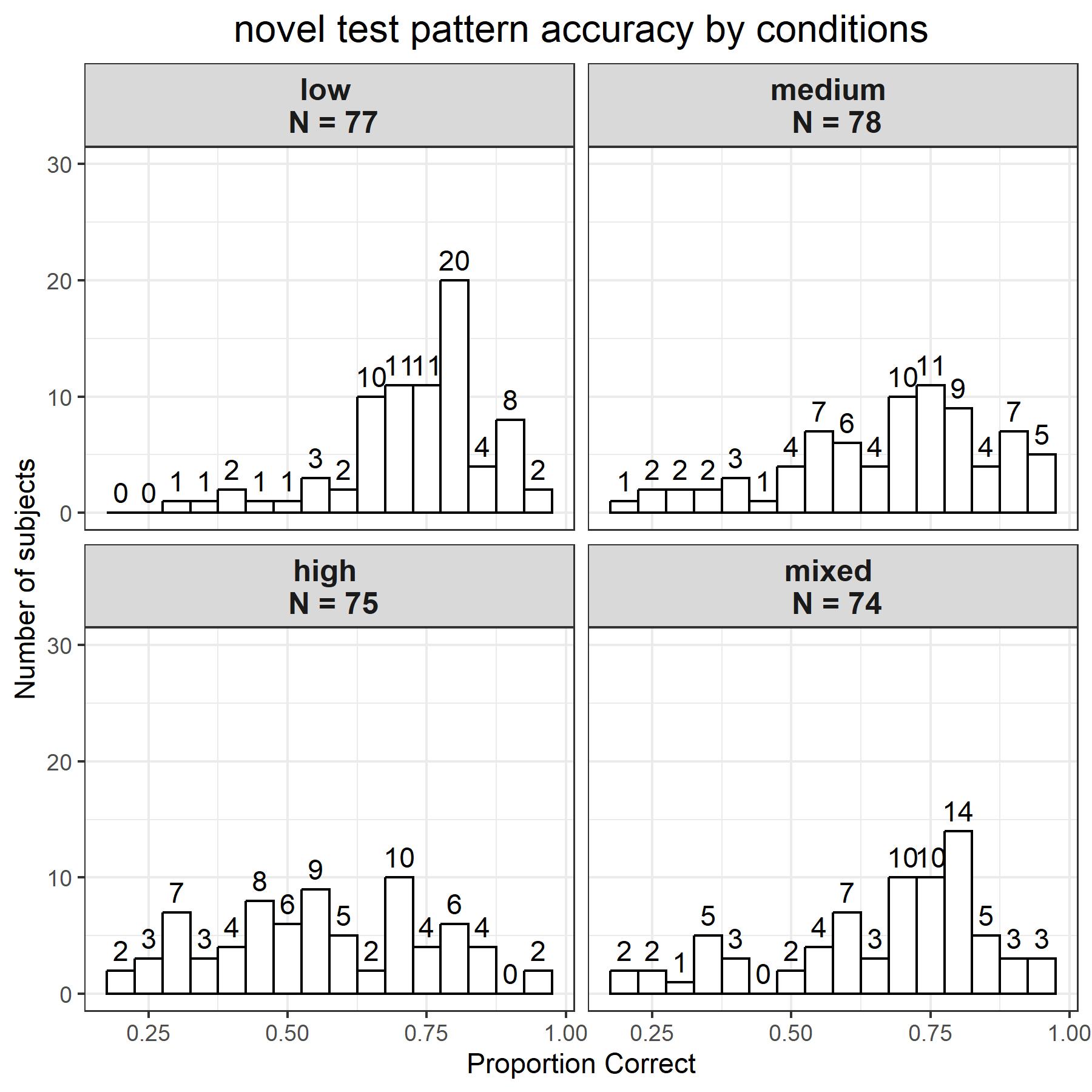


Figure 3

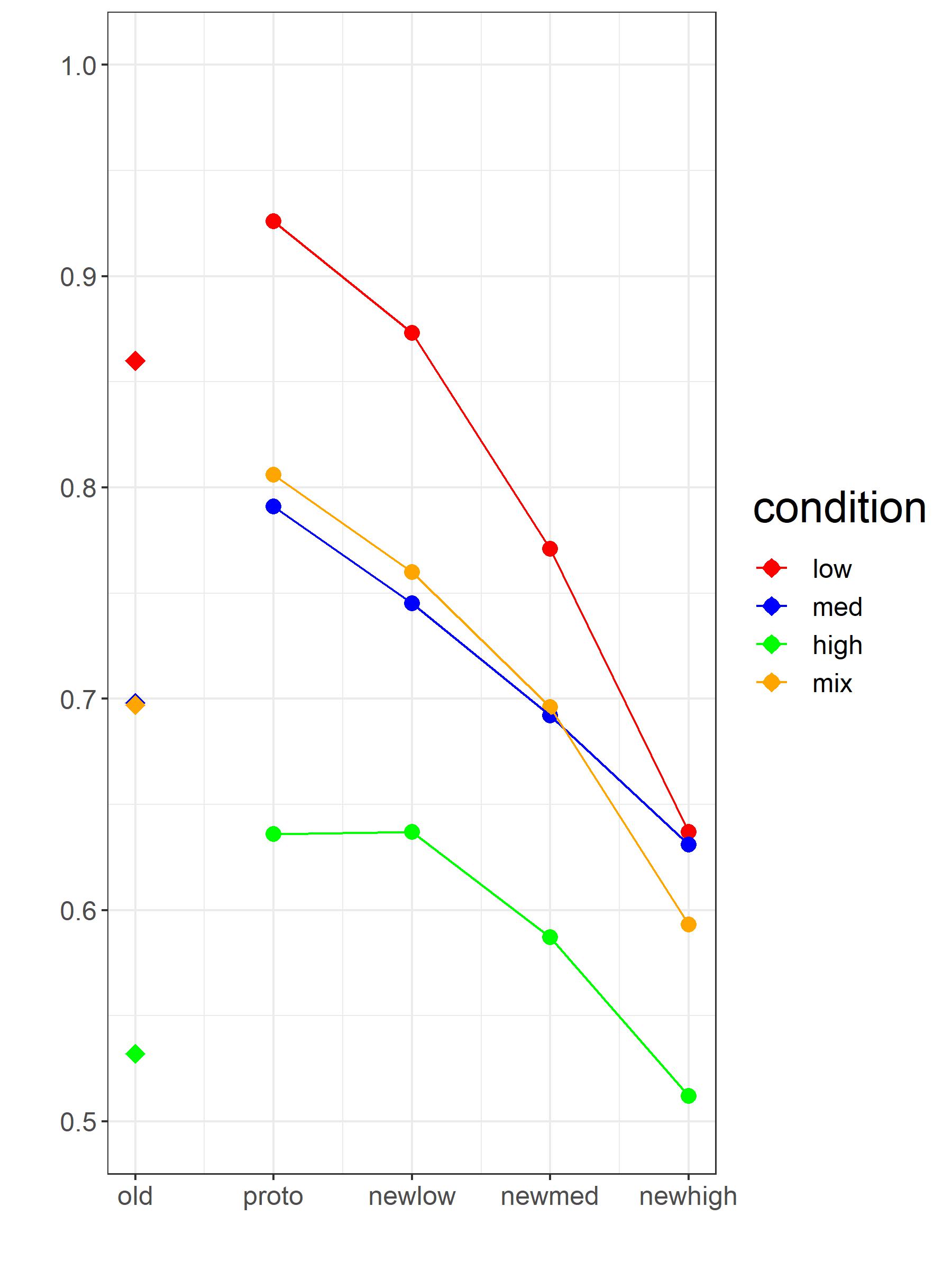


Figure 4