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Learning-induced uncertainty reduction in perceptual decisions is task-dependent

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of different perceptual decision tasks can var at different stages. Therefore, it is reasonable to expect that the neural representation of decision uncertaint is also task-dependent and can be attributed to different stages of decision-making. In fact, our previous functional magnetic resonance imaging (fMRI) stud investigated uncertaint modulation in two perceptual decision tasks, and we demonstrated the task-dependent uncertaint modulation in the human brain (Li and Yang, 2012). In this stud , the participants performed two categorization tasks that required either ne discrimination (i.e., the criterion comparison task) or signal extraction (i.e., the signal detection task). The criterion comparison task required participants to compare clear global patterns with an implicit decision boundar de ned b experimenter (Li et al., 2009, 2012). In the signal detection task, the participants were required to extract the global form from its nois background (Ma hew et al., 2012). We identi ed the areas responsible for performance monitoring, such as the posterior medial frontal cortex (pMFC), as the common hubs for representing uncertaint modulation (Ridderinkhof et al., 2004). Importantl , we also identi ed dissociable cortical networks that were correlated with uncertaint modulation in different tasks. In the criterion comparison task, uncertaint modulated the fMRI activit of areas related to rule retrieval, whereas in the signal detection task, uncertaint modulated the fMRI activit of higher visual areas.

Previous studies have shown that perceptual training is known to improve the performance of perceptual decisions (Sagi and Tanne, 1994; Ghose, 2004; Sasaki et al., 2010). Investigating the effect of perceptual training can also inform the mechanisms underl ing the decision-making process. The relationship between perceptual training and uncertaint reduction of perceptual decisions is an interesting issue to address. Particularl , understanding the task-dependenc of the reduction of different t pes of uncertaint is critical for the evaluation of perceptual training ef cienc . Dosher and Lu (2005) have shown that the abilit to lter external noise in stimuli can be improved b training on both the clear and nois displa s in a Gabor orientation discrimination task. However, onl training effect on the clear displa s can be generalized to the nois displa s, but not vice versa. The as mmetric transfer of training effect was attributed to the limited enhancement of stimulus signal in neural s stem when training was applied to the nois displa s, as amplif ing the stimulus would amplif the signal and external noise together (Dosher and Lu, 1998, 2005). Nevertheless, whether their results can be generalized to high level visual perception, such as pattern categorization, and how the uncertaint on decision criterion changes with training remain less well-understood. To investigate the training effect on uncertaint reduction in the present stud , we trained the participants on either the criterion comparison task or the signal detection task and tested their behavioral performance on both tasks after the training. Moreover, we tted the behavioral data with a model that incorporated both the criterion and signal uncertainties. Our results showed that the learning effect indexed as the categorization accurac transferred from the criterion comparison task to the signal detection task, but not vice versa. Furthermore, the results from the model tting revealed that the signal uncertaint could be reduced b training in both tasks, but the reduction of criterion uncertaint was observed onl after training in the criterion comparison task.

METHODS

PARTICIPANTS

Twent six (10 males, mean age: 21.6, range: 18 25 ears) right-handed, health students from Peking Universit participated in the stud . All participants had normal or corrected to normal vision and gave written informed consent. The experiment was approved b the local ethics committee. All participants were paid equall for their participation.

STIMULI

Glass patterns were used as stimuli in the experiment (Li and Yang, 2012). Each pattern consisted of 600 white dipoles randoml distributed in a square aperture (7.3° × 7.3°) on a black background. The distance between the two dots in a dipole was 15.4 arc min, and each dot was one pixel in size. For each dot dipole, the spiral angle was de ned as the angle between the hidden line linking the two dots of the dipole and the radius from the center of the stimulus aperture to the center of the dipole. The proportion of dipoles aligned according to a speci ed spiral angle (i.e., the signal dipoles) was de ned as the signal level for each stimulus. The spiral angles were randoml assigned for the noise dipoles. The global percept of a Glass pattern was determined b the spiral angle of the signal dipoles. As the spiral angle increased from 0° to 90°, the global percept of the pattern graduall changed from radial to concentric.

B manipulating the spiral angle and the signal level, we constructed two stimulus sets (**Figure 1**). For the criterion comparison set, stimuli were generated between radial and concentric patterns b parametricall var ing the spiral angles from 0° (radial pattern) to 90° (concentric pattern). All stimuli were presented at the 100% signal level. For the signal detection set, perceptual uncertaint was created b manipulating the signal-to-noise ratio. Thus, stimuli were presented at either 0° (radial pattern) or 90° (concentric pattern) spiral angles, and the signal level ranged from 0 to 100%. The criterion uncertaint was operationall de ned as the angular difference between the presented stimulus and the decision boundar (i.e., the criterion to be compared). The signal uncertaint was operationall de ned as the noise level for the given stimulus. Thus, the sources of decision uncertaint for the criterion comparison and signal detection tasks mainl originated from the criterion and signal uncertainties. We speci call selected parameter levels for each task. In the criterion comparison task, we selected ten levels of spiral angles: 23, 32, 38, 41, 43, 47, 49, 52, 58, and 67°. In the signal detection task, we selected 10 different levels: radial patterns at 5%, 9%, 16%, 28%, 48% signal strength, and concentric patterns at 5%, 9%, 16%, 28%, 48% signal strength. These parameter levels are chosen based on pilot experiment results so that uncertaint levels matched in dif cult between different tasks.

PROCEDURE

Participants were randoml assigned to either the criterion comparison group, in which the were trained on the categorization task based on the criterion comparison stimulus set, or to the

Single-Simple Mo el

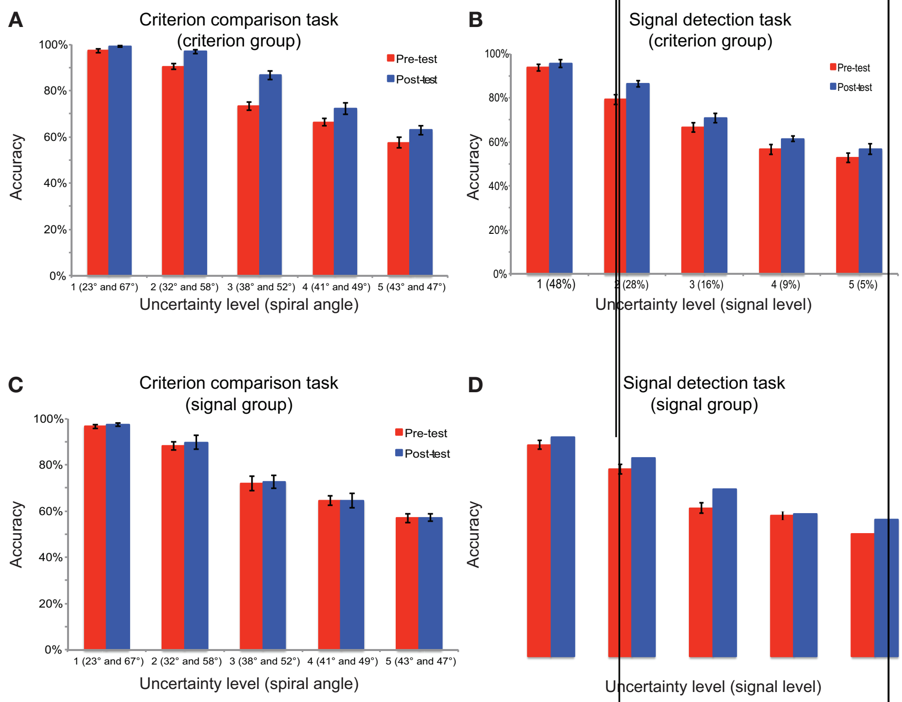
Onl the signal uncertaint with an exponential deca function of signal strength was tted in the model. The decision criterion c_i was a single value. There were three free parameters: the α and β for the exponential deca function and the value of the decision criterion c_i.

We tted the candidate models with the Maximum Likelihood Estimation method. In each trial, a stimulus with a spiral angle θ_i and signal level s_i was presented. The perceived spiral angle p_i was a sample drawn from a Gaussian distribution whose mean was θ_i and whose variance was σ_i, namel $p_i \sim N(\theta_i,\ \sigma_i^2)$.

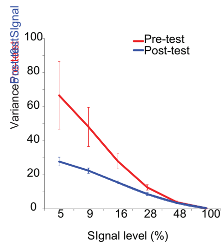
In the Single-Full Model and the Single-Simple Model, the decision criterion was a single value c_i. If $p_i > c_i$, the stimulus was categori ed into a concentric group. Namel , the probabilit of reporting a concentric group was:

$$p(concentric) = \int_{c}^{90} \frac{1}{\sigma_i\sqrt{2\pi}} e^{-\frac{(p_i-\theta_i)^2}{2\sigma_i^2}} dp_i$$

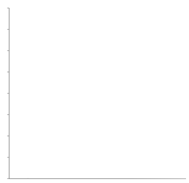
In the Double-Full Model and Double-Simple Model, the perceived spiral angle p_i was a sample drawn from a Gaussian distribution as mentioned above. The decision criterion, c_i, was also a sample drawn from a Gaussian distribution whose mean and variance were μ_i σ l34(8)7(f8:3199...


A
Criterion comparison task
(criterion group)
Pre-test
Post-test
Accuracy
100%
80%
60%
40%
20%
0%
1 (23° and 67°)
2 (32° and 58°)
3 (38° and 52°)
4 (41° and 49°)
5 (43° and 47°)
Uncertainty level (spiral angle)
B
Signal detection task
(criterion group)
Pre-test
Post-test
Accuracy
1 (48%)
2 (28%)
3 (16%)
4 (9%)
5 (5%)
Uncertainty level (signal level)
C
Criterion comparison task
(signal group)
Pre-test
Post-test
Accuracy
Uncertainty level (spiral angle)
D
Signal detection task
(signal group)
Accuracy
Uncertainty level (signal level)

A



B



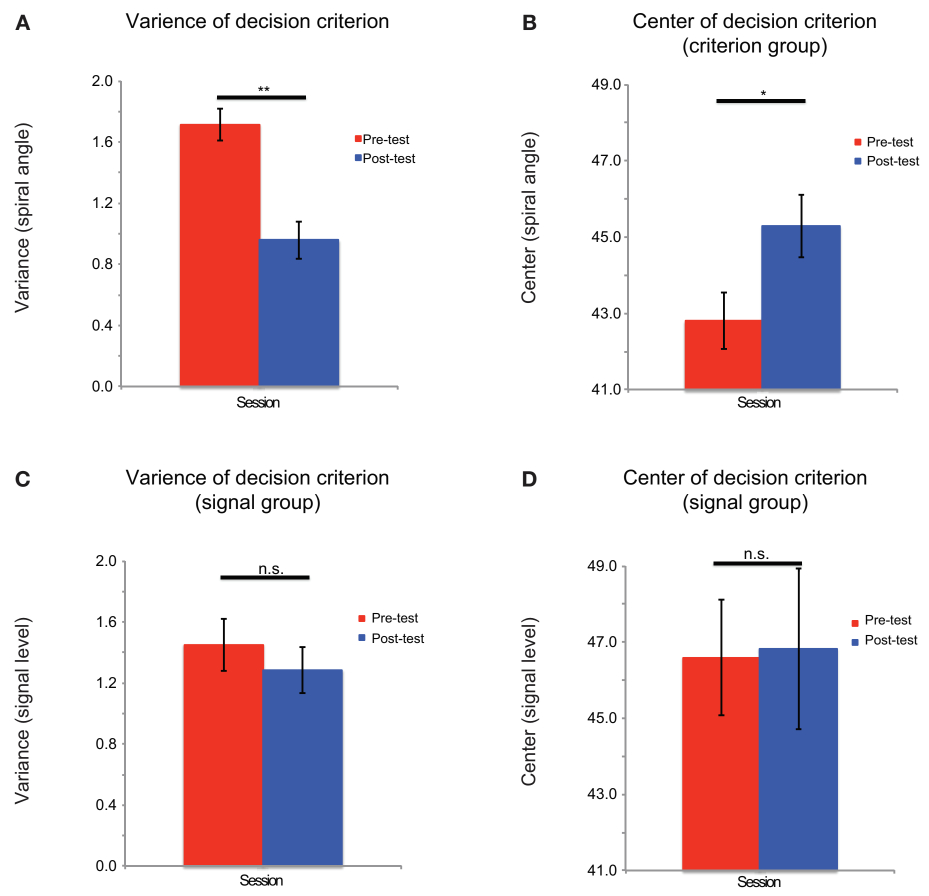


FIGURE 6 | Model fitting results for the criterion uncertainty. The criterion uncertainty is indexed by the variance of decision criterion. The fitting results are shown for **(A)** the variance of the decision criterion distribution of criterion comparison group, **(B)** the mean of the decision criterion of the criterion comparison group, **(C)** the variance of the decision criterion distribution of signal detection group, and **(D)** the mean of the decision criterion of the signal detection group. Error bars represent the standard errors of the means. $^{**}p < 0.01$; $^{*}p < 0.05$; n.s.: not significant.

Finall , our results were unlikel due to differences in task dif cult between the criterion comparison and signal detection tasks. We adaptivel adjusted the stimuli and matched the performance across training sessions and participants. Furthermore, we adopted a single task framework to investigate both the criterion and signal uncertainties, ruling out the possible confounding factors such as task designs and qualitative differences in the stimuli. In summar , our ndings provide evidence that the uncertaint in perceptual decision-making processes can be reduced with training but that the transfer of the uncertaint reduction exists onl from the criterion to signal uncertaint .

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