

# Visual perceptual learning modulates decision network in the human brain: The evidence from psychophysics, modeling, and functional magnetic resonance imaging

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Perceptual learning refers to improved perceptual performance after intensive training and was initially suggested to reflect long-term plasticity in early visual cortex. Recent behavioral and neurophysiological evidence further suggested that the plasticity in brain regions related to decision making could also contribute to the observed training effects. However, how perceptual learning modulates the responses of decision-related regions in the human brain remains largely unknown. In the present study, we combined psychophysics and functional magnetic resonance imaging (fMRI), and adopted a model-based approach to investigate this issue. We trained participants on a motion direction discrimination task and fitted their behavioral data using the linear ballistic accumulator model. The results from model fitting showed that behavioral improvement could be well explained by a specific improvement in sensory information accumulation. A critical model parameter, the drift rate of the information accumulation, was correlated with the fMRI responses derived from three spatial independent components: ventral premotor cortex (PMv), supplementary eye field (SEF), and the frontoparietal network, including intraparietal sulcus (IPS) and frontal eye field (FEF). In this decision network, we found that the behavioral training effects were accompanied by signal enhancement specific to trained direction in PMv and FEF. Further, we also found direction-specific signal reduction in sensory areas (V3A and MT+), as well as the strengthened effective connectivity from V3A to PMv and from IPS to FEF. These findings provide evidence for the learning-induced decision refinement after perceptual learning and the brain regions that are involved in this process.

## Introduction

Perceptual learning refers to improved perceptual performance after intensive training and was initially suggested to reflect long-term plasticity in early visual cortex. Recent behavioral and neurophysiological evidence further suggested that the plasticity in brain regions related to decision making could also contribute to the observed training effects. However, how perceptual learning modulates the responses of decision-related regions in the human brain remains largely unknown. In the present study, we combined psychophysics and functional magnetic resonance imaging (fMRI), and adopted a model-based approach to investigate this issue. We trained participants on a motion direction discrimination task and fitted their behavioral data using the linear ballistic accumulator model. The results from model fitting showed that behavioral improvement could be well explained by a specific improvement in sensory information accumulation. A critical model parameter, the drift rate of the information accumulation, was correlated with the fMRI responses derived from three spatial independent components: ventral premotor cortex (PMv), supplementary eye field (SEF), and the frontoparietal network, including intraparietal sulcus (IPS) and frontal eye field (FEF). In this decision network, we found that the behavioral training effects were accompanied by signal enhancement specific to trained direction in PMv and FEF. Further, we also found direction-specific signal reduction in sensory areas (V3A and MT+), as well as the strengthened effective connectivity from V3A to PMv and from IPS to FEF. These findings provide evidence for the learning-induced decision refinement after perceptual learning and the brain regions that are involved in this process.

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## Materials and methods

### Subjects

(10 ... , 12 ... ; ... : 17–25 ... ) ... A ... A ...

### Stimuli

( ... , ... ) ... (C ... , ... , 1,024 × 768; ... , 60 ... ) ... (C ... ) ... (48- ... , 60 ... ) ... 3.0 ... (B ... , 1997; ... , 1997) ... A AB ( ... A) ... 75 ... 10° ... (~0 / 2). ... 400 ... 4°.

### Procedure

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$\hat{a}$  is a vector of parameters to be estimated. The model is written as  $y = X\beta + \epsilon$ , where  $y$  is the response vector,  $X$  is the design matrix,  $\beta$  is the vector of parameters, and  $\epsilon$  is the error vector. The least squares estimator of  $\beta$  is given by  $\hat{\beta} = (X^T X)^{-1} X^T y$ . The variance-covariance matrix of  $\hat{\beta}$  is  $\text{Cov}(\hat{\beta}) = \sigma^2 (X^T X)^{-1}$ . The standard error of the estimate is  $\hat{\sigma} = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$ . The confidence interval for  $\beta_j$  is  $\hat{\beta}_j \pm t_{\alpha/2, n-1} \text{SE}(\hat{\beta}_j)$ . The F-test for the overall significance of the regression is  $F = \frac{R^2 / k}{(1 - R^2) / (n - k - 1)}$ , where  $R^2$  is the coefficient of determination,  $k$  is the number of predictors, and  $n$  is the sample size. The p-value for the F-test is  $P(F > F_{obs})$ . The adjusted R-squared is  $\bar{R}^2 = 1 - \frac{(1 - R^2)(n)}{n - k - 1}$ . The Akaike Information Criterion (AIC) is  $AIC = -2 \ln L(\hat{\beta}) + 2k$ , where  $L(\hat{\beta})$  is the log-likelihood function. The Bayesian Information Criterion (BIC) is  $BIC = -2 \ln L(\hat{\beta}) + k \ln n$ . The Schwarz Criterion (SC) is  $SC = -2 \ln L(\hat{\beta}) + k \ln n$ . The Hannan-Quinn Criterion (HQ) is  $HQ = -2 \ln L(\hat{\beta}) + k \ln \ln n$ . The Consistent Akaike Information Criterion (CAIC) is  $CAIC = -2 \ln L(\hat{\beta}) + k \ln n$ . The Hannan-Quinn Criterion (HQ) is  $HQ = -2 \ln L(\hat{\beta}) + k \ln \ln n$ . The Consistent Akaike Information Criterion (CAIC) is  $CAIC = -2 \ln L(\hat{\beta}) + k \ln n$ .

**fMRI data preprocessing**

The fMRI data preprocessing pipeline involves several steps: slice timing correction, motion correction, slice-to-volume registration, spatial smoothing, high-pass filtering, and general linear model (GLM) fitting. The slice timing correction is performed using the sinc interpolation method. The motion correction is performed using the rigid body registration method. The slice-to-volume registration is performed using the sinc interpolation method. The spatial smoothing is performed using the Gaussian kernel method. The high-pass filtering is performed using the Butterworth filter method. The GLM fitting is performed using the least squares method. The resulting beta maps are then used for statistical parametric mapping (SPM) to identify significant clusters. The SPM analysis involves thresholding the beta maps at a certain level (e.g.,  $p < 0.001$ ) and then applying a false discovery rate (FDR) correction to control for multiple comparisons. The resulting significant clusters are then reported in terms of their coordinates, volume, and peak intensity.



**Learning effects on drift rate**

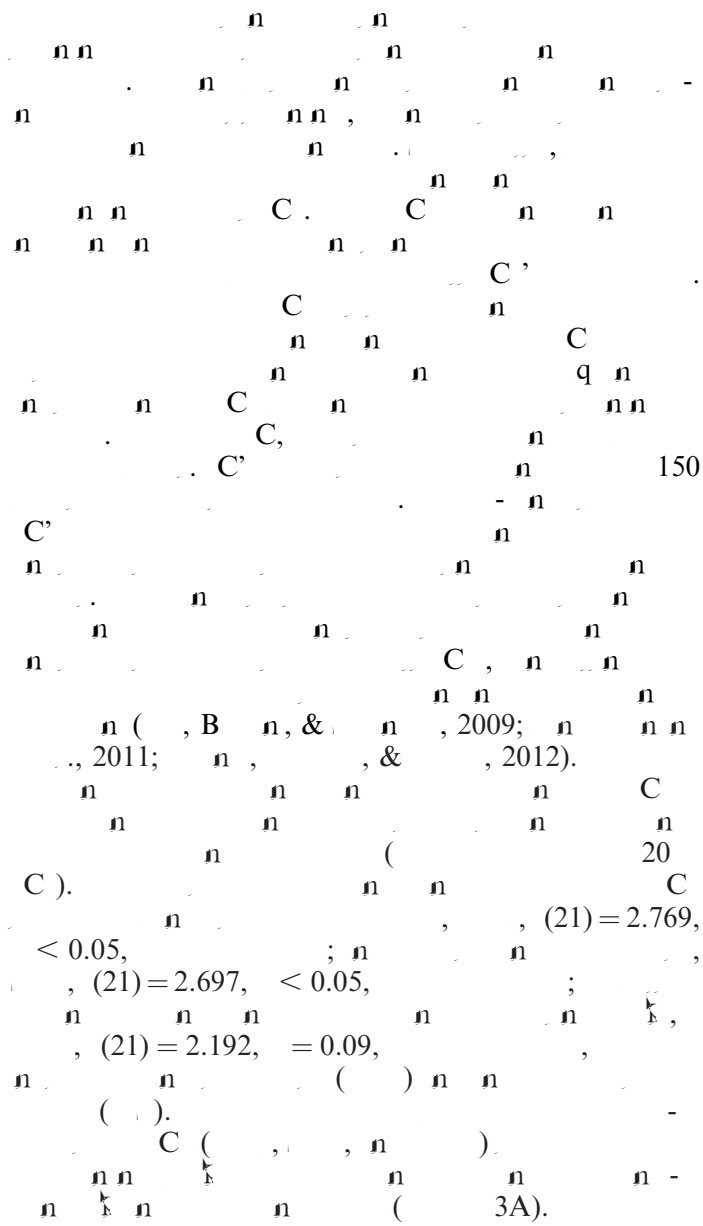
$F(1, 21) = 15.60, p = 0.001, \eta^2 = 0.426;$   
 $F(1, 21) = 48.27, p < 0.001, \eta^2 = 0.697;$   
 $F(1, 21) = 25.43, p < 0.001, \eta^2 = 0.548.$   
 $F(1, 21) = 27.22, p < 0.001,$   
 $F(1, 21) = 0.08, p = 0.78.$   
 (C. C. & , 2012;  
 2011). , 2012) (  
 $b, n$  ( $b - a/2$ ).  
 $F(3, 12) = 15.48, p < 0.001, R^2 = 0.67; \beta = 0.73,$   
 $0.001, n, \beta = 0.214, = 0.26, n, \beta = -0.01, = 0.97.$

**Session effect on decision caution**

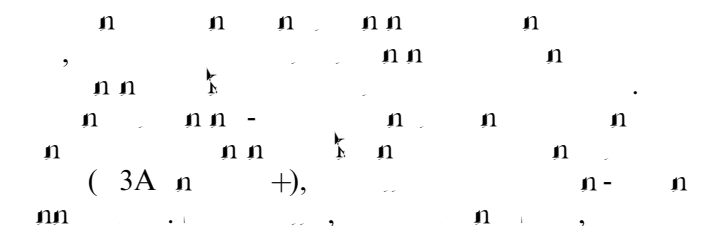
$F(1, 21) = 8.45, p < 0.01, \eta^2 = 0.287$   
 $= 0.97, p < 0.001,$   
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**Brain network for sensory information accumulation**



**Learning effects within decision network**





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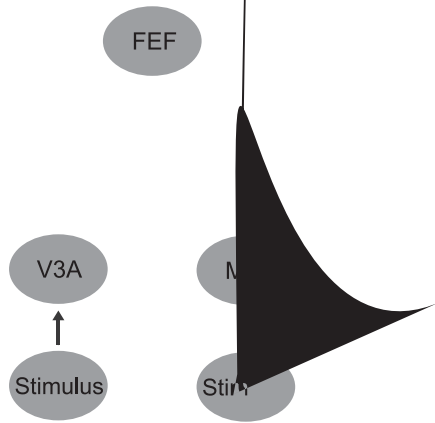
$\eta^2 = 0.315$ ,  $F(1, 21) = 9.652$ ,  $p = 0.005$ ,  $\eta^2 = 0.315$ .

$F(1, 21) = 9.652$ ,  $p = 0.005$ ,  $\eta^2 = 0.315$ .

**Learning modulates feedforward connectivity**

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The first part of the paper discusses the theoretical background of the research, including the concept of *3A* and its relationship to other variables. The second part describes the methodology used in the study, including the sample and data collection procedures. The third part presents the results of the study, including the findings of the regression analysis and the mediation model. The final part discusses the implications of the findings and provides conclusions.

The study was conducted using a cross-sectional design. The sample consisted of *n* participants who were recruited through various channels. The data were analyzed using structural equation modeling (SEM) and mediation analysis. The results showed that *3A* had a significant positive effect on the outcome variable, and this effect was mediated by *C*. The findings suggest that *3A* is an important factor in explaining the variance in the outcome variable.

The study has several limitations, including the cross-sectional design and the potential for common method variance. Future research should investigate the longitudinal relationships between the variables and explore the underlying mechanisms of the mediation process.

In conclusion, the study provides evidence for the role of *3A* in the relationship between *A* and *B*. The findings have practical implications for understanding the factors that influence the outcome variable and for developing interventions to improve it.

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