Distinct Microstructural Brain Correlates of Inter-individual Differences in Reward Learning and Decision-Making

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Abstract

Humans learn which actions yield the highest rewards through trial and error, forming expectations over time. Yet, people often make suboptimal decisions, partly due to noise in how they learn action values. Such learning processes are implicated in several psychiatric conditions.

In a large-scale study, participants completed a gamified reward learning task and surveys measuring impulsivity (using BIS) and compulsivity (using OCI-R). Additionally, they underwent quantitative MRI scanning, in which we measured whole-brain microstructural indices of myelination, myeloarchitecture, and cortical iron. Voxel-based quantification analyses revealed that greater myeloarchitectural integrity, particularly in the left angular gyrus and right postcentral gyrus, correlated with higher learning rates for both chosen and unchosen objects. Learning noise was associated with R1 and R2* values in the precentral gyrus and cerebellum. Impulsivity and compulsivity showed distinct relationships with brain regions, such as the cerebellum, frontal gyrus, and insula. These findings highlight the role of brain microstructure in shaping reward-guided learning and individual differences in impulsivity and compulsivity, with implications for psychiatric disorders.

Keywords: VBQ; Adaptive Behaviour; Reward Learning; Individual Differences

Introduction

Humans learn to optimize actions and decisions through trial and error (Sutton & Barto, 1998). In ideal conditions, we often choose the option leading to the highest reward. However, humans often make suboptimal decisions. While this has traditionally been explained by the exploration–exploitation trade-off, recent research suggests that such behavior may instead reflect noise and limited computational precision in reward-guided learning (Findling et al., 2019). Maladaptive reward learning has been implicated in psychiatric disorders such as OCD and ADHD, particularly in relation to compulsivity and impulsivity. A recent study found that impulsivity is associated with imprecision across valence domains, whereas compulsivity is linked to increased choice stochasticity (Skvortsova & Hauser, 2022).

In this study, we investigated the microstructural brain correlates of computational parameters from a noisy reward learning paradigm, along with measures of impulsivity and compulsivity. This work aims to shed light on the biological basis of individual differences in adaptive behavior.

Methods

565 (360 females, 205 males) participants (median age = 24, age range = 18 - 56) took part in a large-scale neuroimaging project. Participants completed a range of online surveys, cognitive and

behavioral tasks, and MRI scans. Here, we focus on the gamified online tasks as well as the quantitative MRIs. 303 participants completed the gamified tasks, and the overlapping sample between tasks and scans consists of 248 participants. Participants completed a gamified version of a reward learning task. Participants were asked to choose between two objects which would give them different amounts of reward. The goal of the participant was to figure out which object provided the most reward at any given time. The levels of reward fluctuated throughout the trial.

In a separate session participants underwent a quantitative MRI, generating three different map types; MT, R1 and R2*, on which we performed voxel based quantification analysis (VBQ).

Results

To investigate the neurobiological correlates of inter-individual variability in reward learning, impulsivity, and compulsivity, we related model parameters (learning rates for the chosen and unchosen object, learning noise and choice stochasticity) to brain microstructure.

Learning Rates: We found that MT saturation in the left angular gyrus (k = 262; pFWEcorr = 0.03; peak voxel coordinates: x = 48 y = 61 z = 30) positively correlated with the learning rate for the chosen object. MT saturation also correlated with the learning rate for the unchosen object in the right postcentral gyrus (k = 2091; pFWEcorr < 0.001; peak voxel coordinates: x = 35 y = 26 z = 69) and right inferior temporal gyrus (k = 861; pFWEcorr < 0.001; peak voxel coordinates: x = 57 y = -19 z = -32) (see Figure 1 for full results). This suggests that greater myeloarchitectural integrity is linked to higher learning rates for both chosen and unchosen objects. R1 in the left lateral orbital gyrus (k = 318; pFWEcorr = 0.008; peak voxel coordinates: x = -37 y = 34 z = −11) also correlated with the unchosen object's learning rate. Finally, R2* in the right frontal gyrus (k = 2180; pFWEcorr < 0.001; peak voxel coordinates: x = 25 y = -2 z = 49) was correlated with the chosen object's learning rate.

Learning Noise: R1 values in the left precentral gyrus (k = 2661; pFWEcorr < 0.001; x = -2 y = -24 z = 73) and right cerebellum (k = 13212; pFWEcorr < 0.001; peak voxel coordinates: x = 13 y = -59 z = −50) were positively correlated with learning noise. R2* values in the left precentral gyrus (k = 3778; pFWEcorr < 0.001; peak voxel coordinates: x = -4 y = -22 z = 70) also showed a positive correlation with learning noise.

Choice Stochasticity: R1 values in the left precentral gyrus (k =1629; pFWEcorr < 0.001; peak voxel coordinates: x = -2 y = -24 z = 70) were negatively correlated with choice stochasticity.

Impulsivity: Impulsivity was positively associated with MT values in the right cerebellum (k = 1069; pFWEcorr < 0.001; peak voxel: x = 39 y = -69 z = -42). It was also positively associated with R1 values in the left supramarginal gyrus (k = 2460; pFWEcorr < 0.001; peak voxel: x = -52 y = -33 z = 30) and right middle frontal gyrus (k = 1866; pFWEcorr < 0.001; peak voxel: x = 28 y = 3 z = 49). For R2*, impulsivity showed a positive association in the right ventral DC (k = 749; pFWEcorr < 0.001; peak voxel: x = 13 y = -12 z = -22) and a negative association in the right medial orbital frontal gyrus (k = 582; pFWEcorr < 0.001; peak voxel: x = 14 y = 47 z = -22).

Compulsivity: For compulsivity, MT values were positively associated with the left inferior insula (k = 561; pFWEcorr < 0.001; peak voxel: x = -31 y = 8 z = 15). Compulsivity was also positively associated with R2* in the left lateral orbital gyrus (k = 364; pFWEcorr = 0.009; peak voxel: x = -42 y = 56 z = -8).

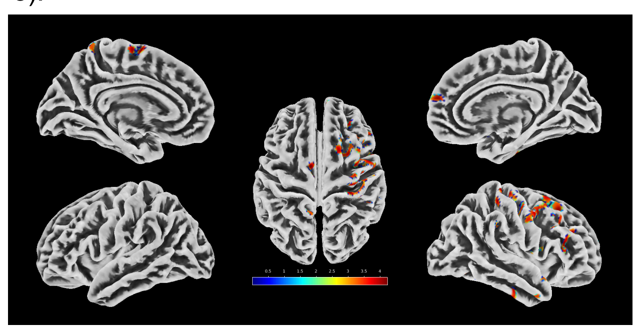

Figure 1: MT values positively associated with the learning rate for the unchosen object across motor sensory and right lateralized frontal regions.

Conclusion

Here, we reveal distinct microstructural correlates of computational parameters in reward learning, with precentral regions indexing learning noise, myeloarchitecture supporting learning rates, and trait dimensions of impulsivity and compulsivity mapping onto frontal and cerebellar structures via both myelin- and iron-sensitive modalities. These findings underscore the involvement of specific brain regions and their microstructural properties in shaping individual differences in reward-guided behavior.

References

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