Passive spatial learning in humans: Neural alignment during naturalistic navigation

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1 Introduction

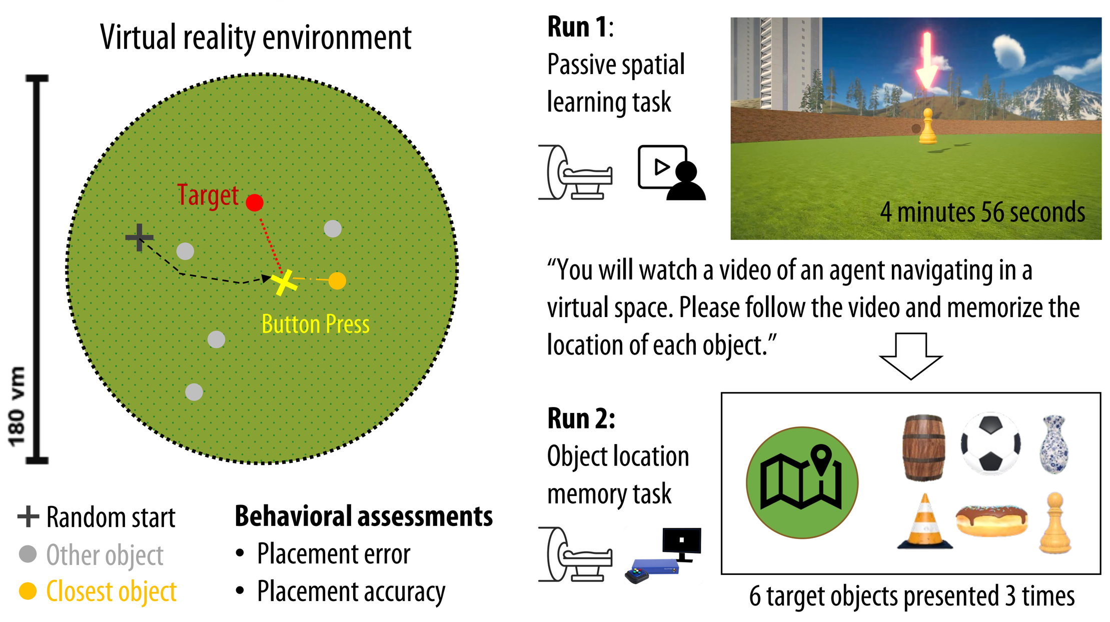
- Learning of spatial environments plays a vital role in the survival of both animal and human species.
- Emerging evidence has highlighted a key navigational neural network in supporting the encoding and internal representation of a cognitive map of our environments during active navigation[1].
- However, the contribution of this network to passive spatial learning (i.e. observer effect) of external environments remains unclear[2].
- Recent work has shown that passive learning from lecture recordings could evoke shared neural representations across participants, with greater alignment to experts linked to better learning outcomes[3].
- Here, we conducted a 3T fMRI experiment using a virtual reality based naturalistic navigation video to investigate the neural mechanism behind passive spatial learning.

Research Objective

The primary goal of our 3T fMRI study was to investigate the alignment of neural responses across participants during passive spatial learning using a virtual reality based naturalistic navigation paradigm, and to predict learning outcomes.

2 Materials and Methods

Experimental paradigm

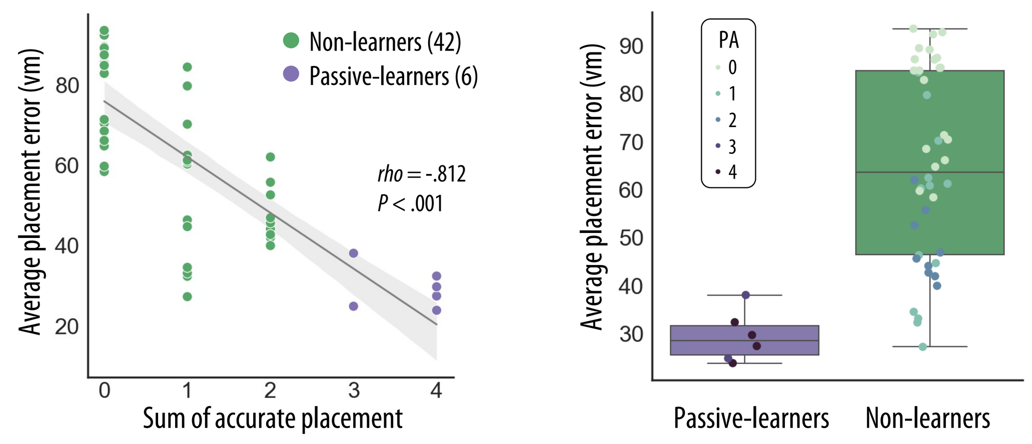


Data collection and behavioral performance

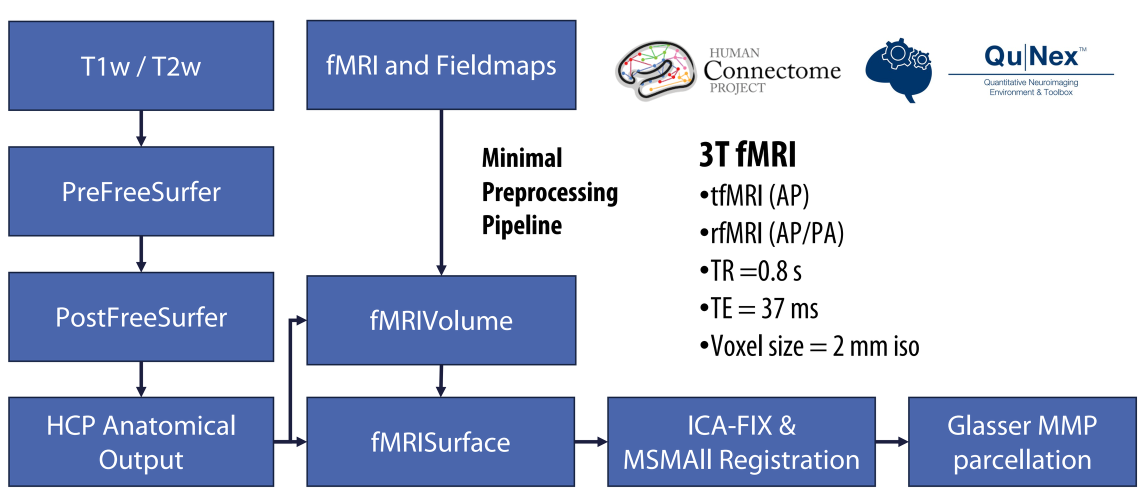
48 healthy participants (age = 23.69 ± 2.15 years; F/M ratio = 30/18)

Definition of passive-learners:

- Average placement error for the first presentations of each object < 40 vm
- Sum of accurate object placement ≧ 3 objects (50% accuracy)

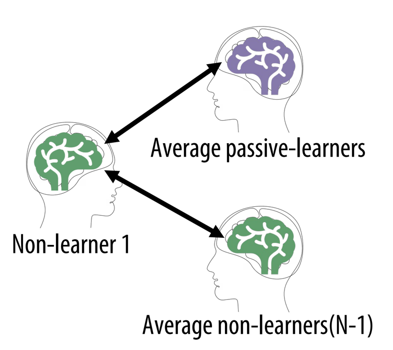


Neuroimaging data preprocessing and analysis pipelines



Inter-subject correlation (ISC) analysis

- Neuroimaging data was minimally preprocessed using HCP pipelines (Qunex[4]) and timeseries were extracted for each Glasser 360 region[5].
- First 5 TRs corresponding to the fixation block were removed (4s).
- Temporal and spatial ISC[6] were calculated via BrainIAK toolbox:
  - For temporal ISC, the timeseries were averaged in each region.
  - For spatial ISC, we calculated the spatial pattern similarity of each region in each event, then averaged them across events.
- Statistical significance with learning outcomes: one-side non-parametric permutation testing (10,000 times) with alpha equals 0.05.



Functional connectivity gradient analysis

- Functional connectivity gradients were extracted via BrainSpace toolbox based on the normalized angle similarity of connectivity profiles using a diffusion map embedding algorithm[7].
- Average passive-learner connectivity matrix was used to generate the template gradient space with 10 dimensions.
- Individual gradients of each non-learner was functionally aligned to the learner template by Procrustes rotation.
- Dispersion was calculated as the Euclidean distance from each region to the origin point in the 2D space defined by top two functional gradients. In addition, individual-template displacement was related to learning outcomes.
- Statistical relationship with learning outcomes: two-sided non-parametric permutation testing (10,000 times).

3 Results

Inter-subject correlation during passive spatial learning

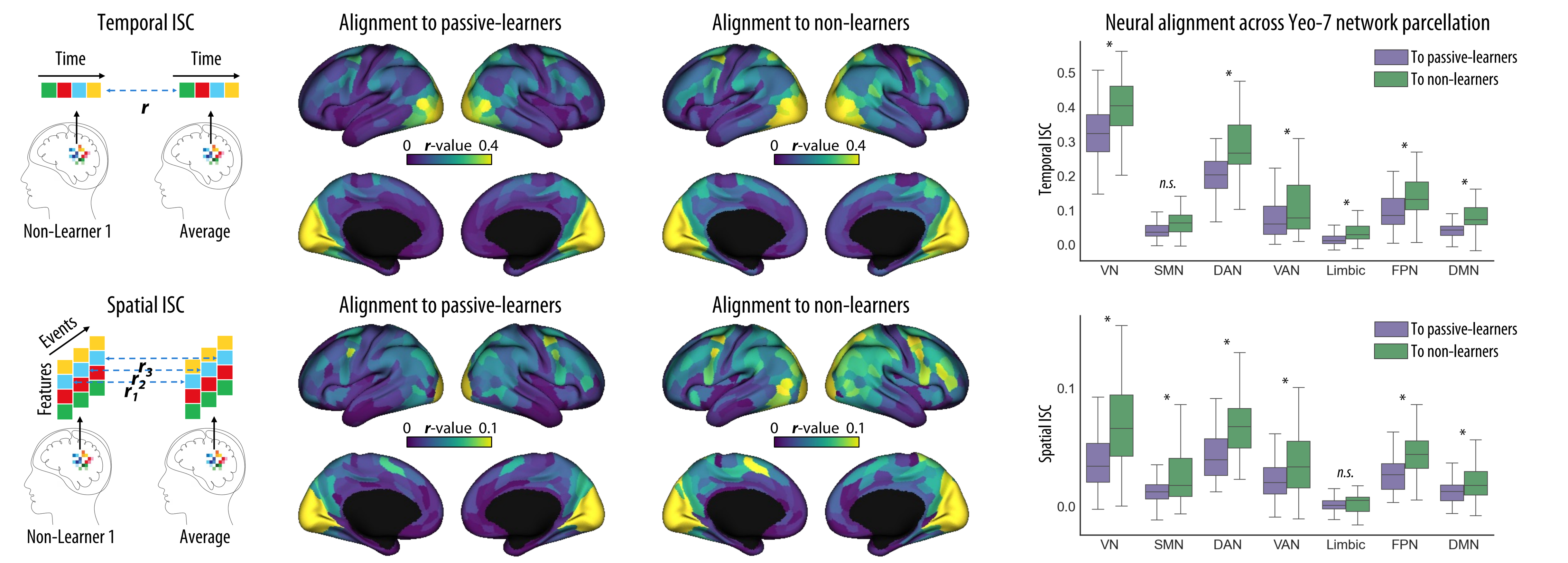


Figure 1. The cortical pattern of neural alignment to passive-learners and non-learners. The neural alignment was calculated for each region by using both temporal timeseries and spatial activity patterns while participants watched a naturalistic navigation video. Overall, the highest alignment across groups was centred on the visual and dorsal attention networks (Tukey's HSD test). Across the two alignment methods, all networks showed a significant reduction in alignment to passive-learners except for SMN and Limbic network, with the highest effect observed in the VN, DAN, FPN and DMN. The 'winner takes all' approach was used to map each MMP regions onto the Yeo-7 network parcellation[8] (VN, visual; SMN, somatomotor; DAN, dorsal attention; VAN, ventral attention; FPN, frontoparietal; DMN, default mode network; **P* < .001; ***n.s.*** denotes no significant difference).

Neural alignment based on functional connectivity gradients

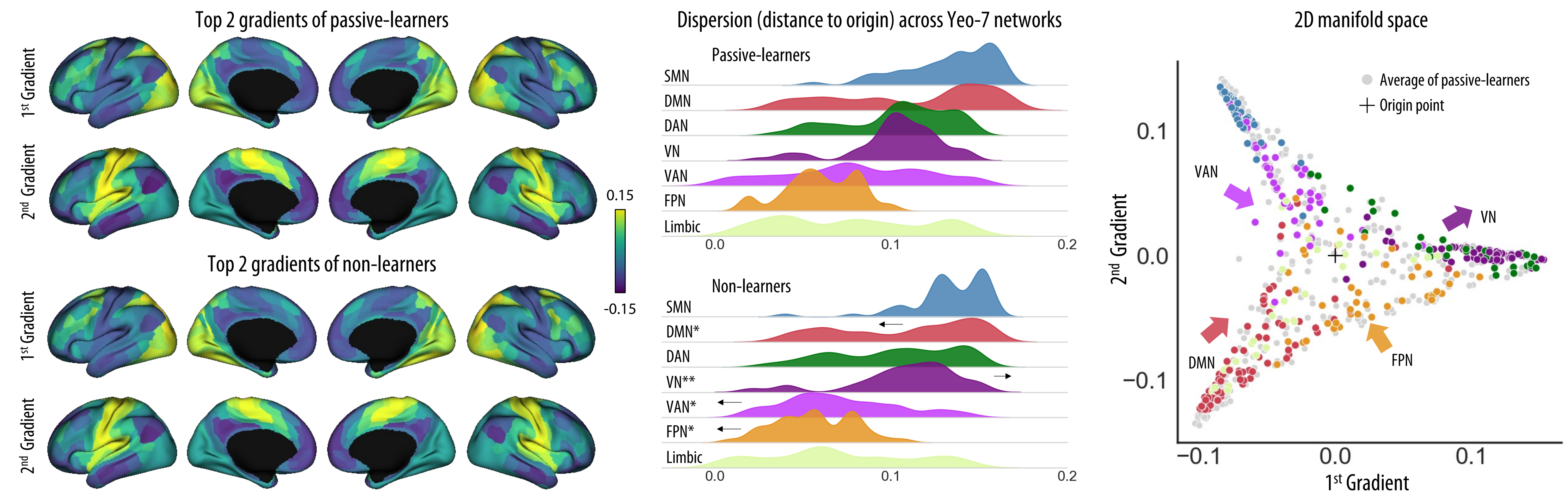


Figure 2. Neural alignment in low-dimensional manifold space. Low dimensional manifolds were derived from the average connectivity matrix of passive-learners. The functional connectivity gradients of non-learners were then aligned to the passive-learners. The first two gradients explained most of the variance of the original space (23% and 22%). The first gradient exhibited an axis that extended from perceptually-oriented cognition (VN and DAN) to memory-based cognition (DMN, VAN, and SMN). On the other hand, the second gradient depicted the separation of DMN and SMN. Network level dispersion revealed shrinkage of the DMN, VN and FPN in non-leaners, with an expansion in VN (**P* < .05, ***P* < .001).

Correlation of neural alignment and learning outcomes in non-learners

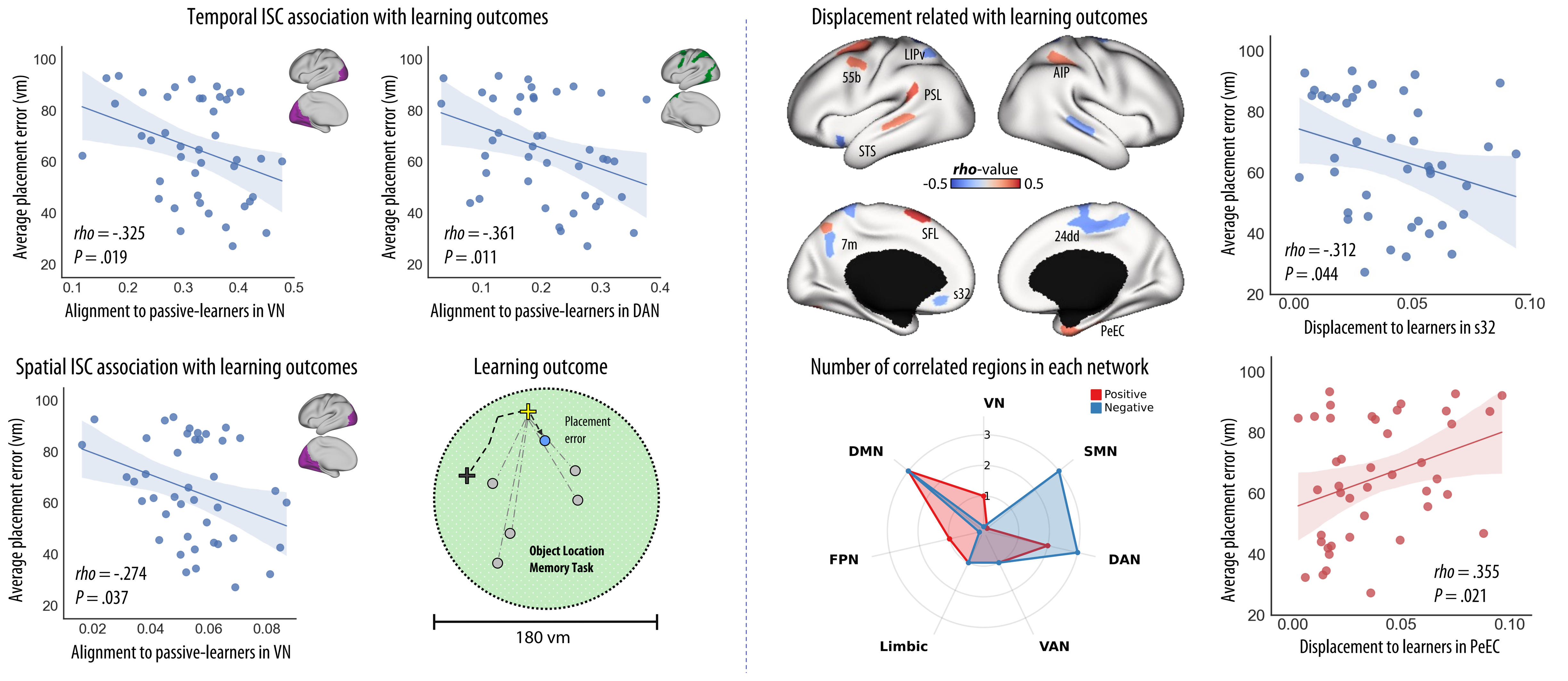


Figure 3. Association of neural alignment with learning outcomes. The correlation analyses revealed neural alignment to passive-learners within the VN and DAN were negatively related to the average placement error (better performance) across the initial presentation of each object in a subsequent active retrieval task (one-sided 10,000 permutation test, ***P*** < .05). Regarding regional displacement in the 2D manifold space in comparison to passive learners, the left perisylvian area (PSL) and the left superior temporal sulcus (STS) in DMN, the left dorsal frontal cortex and the right anterior intraparietal cortex (AIP) in DAN, as well as the perirhinal entorhinal cortex (PeEC) were positively correlated with the average placement error, while negative correlation (better performance) was mainly located in the left posterior cingulate cortex (7m), the left medial prefrontal cortex (s32), and the right paracentral lobule.

4 Conclusions

- The highest neural alignment was centred on the visual and dorsal attention networks, with significantly lower alignment observed to passive-learners in comparison to non-learners.
- Compared to passive-learners, the low dimensional manifold space of non-learners showed significant alterations along two principal axes.
- Neural alignment to passive-learners was associated with subsequent navigation performance, especially for the networks that displayed the greatest neural alignment.
- Collectively, our findings highlight the key roles played by both perceptually-oriented and memory-based brain networks in the passive encoding of spatial memory.

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