Lower-Dimensional, Optimized Representations of High-Level Information in Chess Experts

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Abstract

Chess provides a powerful framework to investigate how expertise shapes neural representations. We conducted an fMRI study with 20 expert and 20 novice chess players who viewed 40 boards that systematically varied across three main feature categories. Using Representational Similarity Analysis (RSA), we found that while both groups encoded low-level visual features similarly, experts showed distinctly more clustered representations of strategic and higher-level properties. A dimensionality compression measure (Participation Ratio) further revealed that experts' neural signals were concentrated in fewer dimensions, suggesting more efficient coding in experts. Taken together, these findings suggest that expertise may result in optimized, lower-dimensional representations within regions involved in both domain-specific (chess-related) and domain-general processing, enabling more effective representations of complex stimuli – which may be the basis of Expertise behavioral effects.

Introduction

It is well-established that experts outperform novices in tasks within their domain of expertise (Chase & Simon, 1973a), yet the neural basis of this advantage remains an open question. Chess, considered a prime example of cognitive expertise (Bilalić, 2017), with its rich history in cognitive and psychological research and the large wealth of available data, is an ideal starting point for our investigation on expertise.

Prior studies indicate that experts differ from novices in eye movements (Bilalić, Langner, Erb, & Grodd, 2010), univariate brain activity (Bilalić et al., 2010; Krawczyk, Boggan, McClelland, & Bartlett, 2011; Bilalić, Turella, Campitelli, Erb, & Grodd, 2012), and cognitive strategies – such as "chunking" the board into familiar groupings (Chase & Simon, 1973b). However, key questions remain: *what* information do experts' brains encode, and *where* in the brain are these representational changes implemented?

Although existing studies identify brain areas involved in chess expertise, they do not directly address what information these areas encode or how these representations differ in experts versus novices. Traditional univariate analyses might miss important changes in representational geometry—cases where the overall activation looks similar, but the underlying activity patterns reveal distinct processing in experts.

In other words, we still need to pinpoint whether experts' neural representations of chess differ systematically from those of novices, which brain regions exhibit these differences, and which stimulus properties drive these changes.

Representational geometry provides a framework to examine this: by looking at the structure of neural activation patterns (for instance, how stimulus representations cluster or separate in neural representational space), we can understand how expertise shapes information processing (Martens, Bulthé, van Vliet, & de Beeck, 2018; Duyck, Martens, Chen, & Op de Beeck, 2021).

In this study, we aim to fill these gaps by using multi-variate techniques – such as Representational Similarity Analysis (RSA) – to investigate how chess expertise alters the representational geometry of neural activation patterns related to chess boards.

Methods

Stimuli The experiment used a set of 40 chess-board stimuli varying along three categories: *Checkmate vs. Non-checkmate* boards, a high-level relational category; *Strategy*, defined by the pieces involved and the complexity of the checkmate (queen–rook mates, queen–rook supported by minor pieces, knight–bishop mates, bishop forcing moves, and simple one-move checkmates). This category reflects both tactical/relational reasoning and a visual component related to piece identity; and *Visual similarity*, where each checkmate has a visually matched non-checkmate differing by a single pawn that disrupts the mate, capturing low-level perceptual properties.

fMRI data collection and analysis We conducted an fMRI study with 40 participants (20 experts, 20 novices). All novices understood chess rules and could identify checkmates and legal moves, but lacked formal training or an Elo rating. Experts

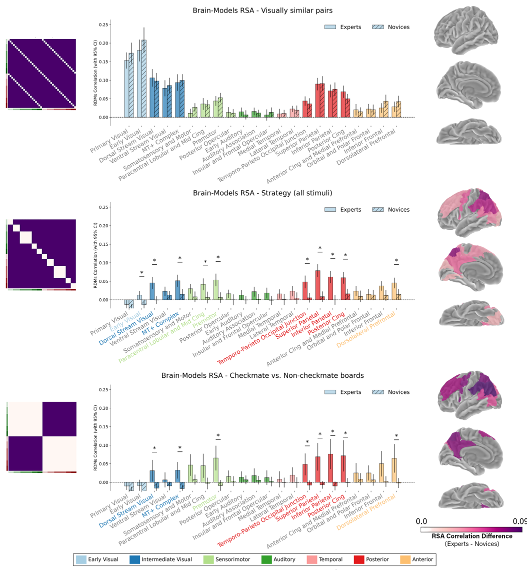

Figure 1: Left: binary (same-different) model RDMs for each category. Axes colors represent Checkmate (green) and Non-Checkmate (red) stimuli, while saturation indicates different strategies. Stimuli are ordered, so that e.g., the the first Checkmate stimulus is visually similar to the first Non-Checkmate stimulus. Center: RSA results. Bars indicate the Pearson correlation between model RDMs and group-averaged RDMs across ROIs for Experts and Novices. Error bars indicate 95% Confidence Intervals. Stars and and colored x-axis labels indicate significant differences (FDR corrected, $p_{FDR} < .05$) between Experts and Novices. Right: Expert - Novices RSA results plotted on pial surface. Only significant ROI differences are shown.

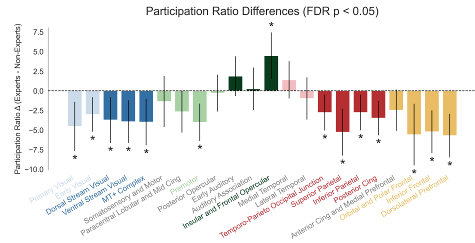

Figure 2: Participation Ratio difference (Experts − Novices) across ROIs. Lower values indicate lower representational dimensionality in Experts. Bars represent 95% Confidence Intervals. Group differences and CIs were computed using independent-samples t-tests assuming unequal variances. Stars represent FDR-corrected significance.

had a rating of 1800 or higher, either official or online. Participants performed a 1-back task, deciding whether the current board was more advantageous than the previous one, over 5–10 scanning runs. FMRI Data was pre-processed with fMRIPrep (Esteban et al., 2017) and analyzed using a First-Level General Linear Model (GLM) in SPM12. The first-level GLM included a separate regressor per trial, resulting in 40 regressors (one per chess board) and 8 nuisance regressors (global signal, 6 motion parameters, frame-wise displacement) per run.

Beta images for the same board were averaged across runs to yield a more reliable subject-level estimate. For each subject, we extracted multi-voxel activation patterns from these run-averaged beta images within specific Regions of Interest (ROIs).

The ROIs were defined via the Glasser parcellation (Glasser et al., 2016), projected into MNI space, and made available as `MNI_Glasser_HCP_2019_v1.0` via `afni_atlases_dist` (AFNI; Cox, 1996). Hemispheric partitions in the AFNI Glasser parcellation were merged into bilateral masks and grouped by the coarse labeling in the original parcellation (Glasser et al., 2016) (see Fig. 1).

We performed two main analyses at the subject level and then averaged the results across participants to compare Experts and Novices: **RSA**, (Kriegeskorte, Mur, & Bandettini, 2008) to characterize the representational geometry within each ROI for both groups, assessing how these patterns relate to the categorical Representational Similarity Matrices (RDMs) derived from our dataset; and **Participation Ratio (PR)** (Altan, Solla, Miller, & Perreault, 2021; Gao et al., 2017) to quantify the degree of information compression in each ROI, evaluating whether expertise is associated with more compact neural representations.

Results

Representational Geometry We constructed Representational Dissimilarity Matrices (RDMs) reflecting the similarity structure predicted for each category and compared them to the brain-derived RDMs for each ROI and subject. Predicted RDMs were binary: pairs from the same label had distance 0; pairs from different labels (e.g., Strategy types, or Checkmate vs. Non-Checkmate) had distance 1. Brain RDMs were estimated using correlation distance between run-averaged ROI data, and compared to the predicted RDMs using Pearson correlation. Higher r between model and brain RDMs indicate higher alignment between the brain's representational geometry and the predicted geometry for that category.

Figure 1 shows that lower-level, perceptual stimulus properties as captured by the visually similar pairs are well represented in both groups, with no significant differences between Experts and Novices. This suggests similar low-level visual processing across groups. In contrast, the "Strategy" and "Checkmate vs. Non-checkmate" categories exhibit stronger correlations in Experts, indicating a stronger representation of these properties in intermediate and high-level regions.

These findings suggest that although both groups exhibit similar geometry for perceptual features, experts' representations are more sensitive to high-level strategic information. These differences are evident in dorsal and medial parietal areas associated with rapid pattern retrieval from long-term memory (Bilalić et al., 2010; Bilalić, 2017), in intermediate visual regions, premotor cortex, and dorsolateral prefrontal areas linked to working memory and executive control.

Dimensionality Compression We computed the PR to estimate dimensionality in the GLM beta images within each ROI. After averaging betas across runs and extracting voxel-wise data, we performed PCA (retaining all possible components, $n-1=39$), and calculated the PR on the resulting matrix. High PR indicates variance spread across many components (high-dimensional representation); low PR indicates variance concentrated in fewer components (low-dimensional representation).

Figure 2 shows the PR difference (Experts − Novices) across ROIs. Most regions exhibit significantly negative values, indicating lower dimensionality in Experts. This aligns with the idea that expert brains compress information into fewer, more efficient representational dimensions.

Conclusions

Our RSA and PR analyses converge on the conclusion that expert chess players exhibit more *compressed* optimal representational manifolds compared to novices. This aligns with prior theoretical frameworks like "chunking" and template theories (Chase & Simon, 1973b; Gobet & Simon, 1996) that predict experts develop more compact neural representations through extensive practice and experience.

Taken together, these findings suggest that expertise leads to more *optimized* representations that likely facilitate rapid encoding and retrieval of chess configurations. This optimization is observable not only in regions encoding domain-specific information (e.g., chess pieces and patterns) but also in general-purpose areas—such as premotor and visual ROIs—implicated in broader aspects of spatial reasoning and motor planning.

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