Unrevealing Neural Factors Underlying Human Intelligence with Large-Scale Functional Neuroimaging Meta-Analysis and Exploratory Factor Analysis

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Abstract

Previous research have reached mixed findings about whether single or multiple latent factors contribute to human intelligence. In order to resolve this conflict, the present study merged brain representational maps for 25 cognitive tasks from Neurosynth and NeuroQuery dataset, and performed exploratory factor analysis to find latent factors that explains the variance between the brain representations of different cognitive tasks. Then we reversely mapped the factor weights onto brain voxels to examine their locations. The results showed that five factors could be extracted, one factor could be viewed as "domain-general" and contributed to different aspects of intelligence, while other four factors are "domain-specific" since each factor corresponded to specific functions including inhibition, episodic memory, emotion, and language. The reverse mapping of these factors further confirmed this finding by showing that "domain-general" factor mainly located in the multiple demand system that previously defined to be closely related with general intelligence, and "domain-specific" factors mainly located on specific brain regions that process related information. For example, episodic memory factor on hippocampus and visual cortex, language factor on auditory cortex and broca area. These findings indicated that both "domain-general" and "domain-specific" factors exist and contribute to human intelligence.

Keywords: Intelligence; Meta-analysis; Factor analysis

Introductions

The cognitive construct and neural substrates underlying human intelligence have been attracting researchers for a long time. The g-factor is a latent factor extracted from behavioral results of different cognitive tasks (Spearman, 1961), and has been shown to closely related to academic success (Rosander et al., 2011). Corresponding to the behavioral g-factor, Duncan (2010) identified multiple demand (MD) system distributedly located in the brain that contributes multiple cognitive processes (Fedorenko et al., 2013).

However, some other studies indicated that human intelligence could not be explained by a single g-factor but multiple latent factors (Visser et al., 2006; Castejon et al., 2010). Furthermore, recent neuroimaging studies also found that besides MD systems, many domain-specific regions actively interact with each other to enable intelligent behavior in different task context (Hampshire et al., 2012; Soreq et al., 2021). Therefore, a mixed finding exist in the cognitive construct and neural substrates of human intelligence.

In the current project, we aimed at resolving the latent structure of human intelligence with factor analysis on large-scale functional neuroimaging meta-analysis. We identified core factors that contributes to the variance of brain representations in different cognitive tasks, and then reversely mapped the factor weights onto brain voxels to understand the functions of the factors (see flow chart in Figure1).

Methods

Data Extraction

We used the latest version of the Neurosynth dataset Yarkoni et al. (2011) and NeuroQuery dataset Dockès et al. (2020). Both of the datasets include more than 13,000 fMRI studies and over 500,000 activation coordinates covering the whole brain. Each of the studies in the databases were represented by a Pubmed ID, peak activation coordinates and weighted topic associations. For selecting appropriate labels for cognitive tasks, we used the task terms in the Cognitive Atlas knowledge base Poldrack et al. (2011).

Multi-Level Kernel Density Analysis

After extracting studies associated with each cognitive tasks, we conducted fMRI meta-analysis using NiMARE v0.0.11 Salo et al. (2022, 2023). Since Neurosynth and NeuroQuery datasets did not provide information for subject number in each study, we used MKDA algorithm Wager et al. (2007) instead of Activation Likelihood Estimation (ALE) or Seed-based Mapping algorithms (SDM) to perform the meta-analysis.

Factor Analysis

The exploratory factor analysis (EFA) results were based on principal component extraction with eigenvalues greater than 1, and a threshold of 0.4 was used to determine the presence of loadings. In the resulting figure, solid lines indicate primary loadings, while dashed lines represent secondary loadings. Factors F1 to F5 are sorted by coefficient magnitude. For a given factor, loadings are sorted from highest to lowest.

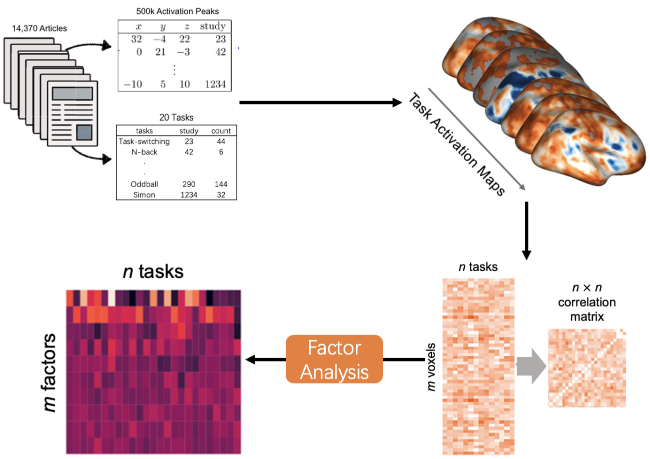

Figure 1: Flow chart of the analysis included in the present study. In general, we first extracted fMRI studies corresponding to each task from the Neurosynth and NeuroQuery dataset. Then we conducted MKDA meta-analysis to calculate brain representation maps for all tasks. After that we used exploratory factor analysis to reveal core factors that explained 50% of the task variance.

Results

Included Studies

According to previous studies, we filtered task terms in Cognitive Atlas that associated with more than 5 studies to generate reliable result maps for each task (Müller et al., 2018). As a result, we included 25 tasks covering tasks that measured different aspects of cognitive processing (e.g., executive functions, episodic memory, emotions, decision-making, and language). The number of studies associated with each term ranged between 6 to 158, with a mean of 62.4 studies. Please see example result maps generated by MKDA algorithm in Figure2.

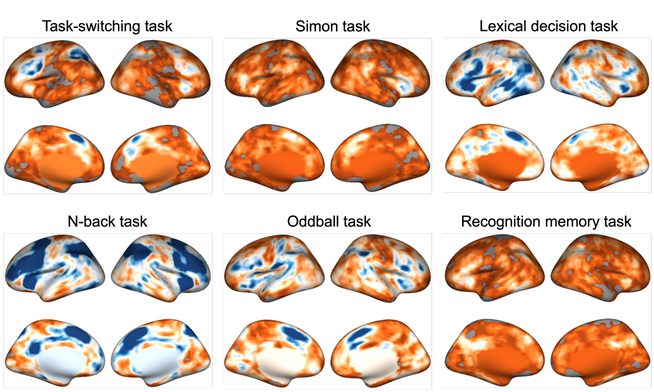

Figure 2: Example brain activation maps for six cognitive tasks generated by MKDA algorithm in NiMARE.

Five Latent Factors Extracted

The results from EFA indicated that five latent factors could be extracted from the brain maps of the 25 cognitive tasks. The F1 explains the most variance (%34) and is associated with task associated with working memory (n-back task), flexibility (task-switching task), attention (selective attention task), episodic memory (recognition memory task) and inhibitory control (stroop task), therefore, F1 could be defined as a general factor that involves in different cognitive processes. The F2 is mainly associated with inhibitory control and decision-making tasks. The F3 is correlated with tasks that measured visual emotions and language. The F4 has high loadings on episodic memory tasks (memory encoding task), and the F5 associates with language tasks (see Figure 3A).

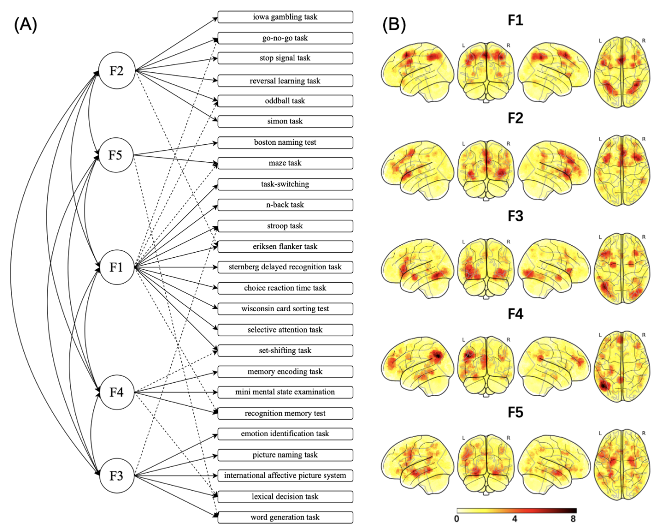

Figure 3: (A) Results from EFA, solid lines represent factor loadings larger than 0.4, while dash lines represent those smaller than 0.4. (B) The spatial mapping of five factors on human brains, the color bar represents the factor weights.

Spatial Mapping Corresponds to Factor Functions

The reverse mapping of factor weights onto brain voxels showed how the latent factors are located on the brain (see Figure 3B). The mapping of F1 shows a large overlap with the MD system (Duncan, 2010), which has been shown to be involved in many cognitive aspects and closely correlated with human intelligence. The dorsal lateral prefrontal cortex (DLPFC) and anterior cingulate cortex showed high weights of F2, which consist with previous findings that DLPFC and ACC are responsible for conflict monitoring (Kerns et al., 2004; Aron et al., 2014) and uncertainty (Krain et al., 2006; Dixon & Christoff, 2014). The F3 mainly located on amygdala that responsible for emotional response and visual cortex. The F4 highly concentrated on visual cortex and hippocampal regions that crucial for episodic memory reactivation (Xue et al., 2010; Kuhl et al., 2012). Finally, auditory cortex and broca area have the highest weights for F5.

Conclusions

The results showed that five factors underlies human intelligence, with one "domain-general "factor that contributed to different aspects of intelligence, while other four "domain-specific" factors that each corresponded to specific functions.

Then, the reverse mapping of these factors further confirmed this finding by showing that "domain-general" factor mainly located in the MD system, and "domain-specific" factors mainly located on specific brain regions that process related information. For example, inhibition and decision-making factor on ACC and DLPFC, emotion on amygdala, episodic memory factor on hippocampus and visual cortex, language factor on auditory cortex and broca area. These findings indicated that both "domain-general" and "domain-specific" neural factors exist and contribute to human intelligence.

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