#2480

Multivariate Analysis of Cortical Morphometry across Human Brain Development

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Introduction

- Understanding patterns of development across measures of brain structure is critical to developing a "normative" mapping that allows us to better understand instances of maladaptive development that lead to neurodevelopmental disorders.
- Recent studies examining multiple cortical neuroanatomical features, have not addressed the differences across whole brain as a function of a specific neuroanatomical feature [1]

- **Aim:** using a matrix decomposition technique [2,3], to investigate the inter-relatedness of morphometric brain features in the context of developing brain anatomy, and how identified patterns are influenced by age, sex and demographics.

Methods

Data: structural MRI, 776 youths (357 F), age range: 5 to 25, (mean age:12.4, SD:3.49) National Institute of Mental Health. (NIMH)
Morphometric Features: Cortical Thickness (CT), Surface Area (SA), local Gyrification Index (GI), and Mean Curvature (MC) extracted over ~80,000 vertices (CIVET 2.1) [3].

- **Workflow**

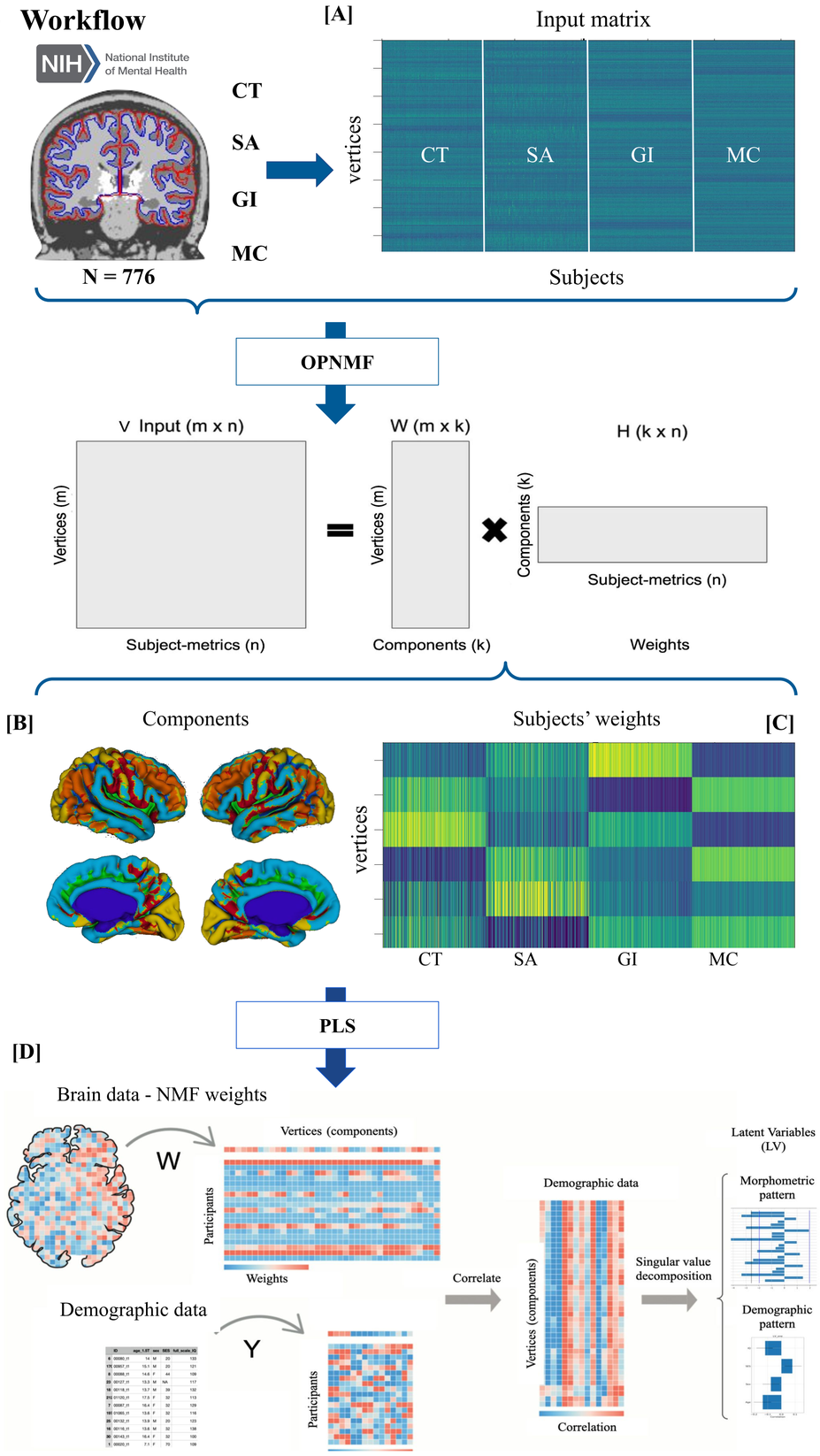

Figure.1) OPNMF: Orthogonal projective nonnegative matrix factorization, decomposes a single input morphometry matrix, composed of vertex-wise measures of subjects' multiple brain morphometric features [**A**], into a matrix describing components of variance [**B**] and another providing subject-specific loading weights onto the spatial components, with respect to each morphometric feature [**C**]. [2,3,5]
PLSc: Partial Least Squares correlation analysis, identifies correlative patterns between brain weights matrix (W) and demographic data (age, sex, IQ, and SES) matrix (Y) through Latent Variables (LV). [**D**] [6]

Selecting the number of components: to balance high stability while capturing major changes in accuracy, a split half stability coefficient and the change in reconstruction errors for a range of (2-20) component decomposition was calculated. [2] See results [**Fig.2, C**]
Multiple linear regression models: We evaluated how individual weightings vary with respect to age and sex using multiple linear regression models corrected for multiple comparisons using the false discovery rate. See results [**Fig.3**]

Results

- **OPNMF results**

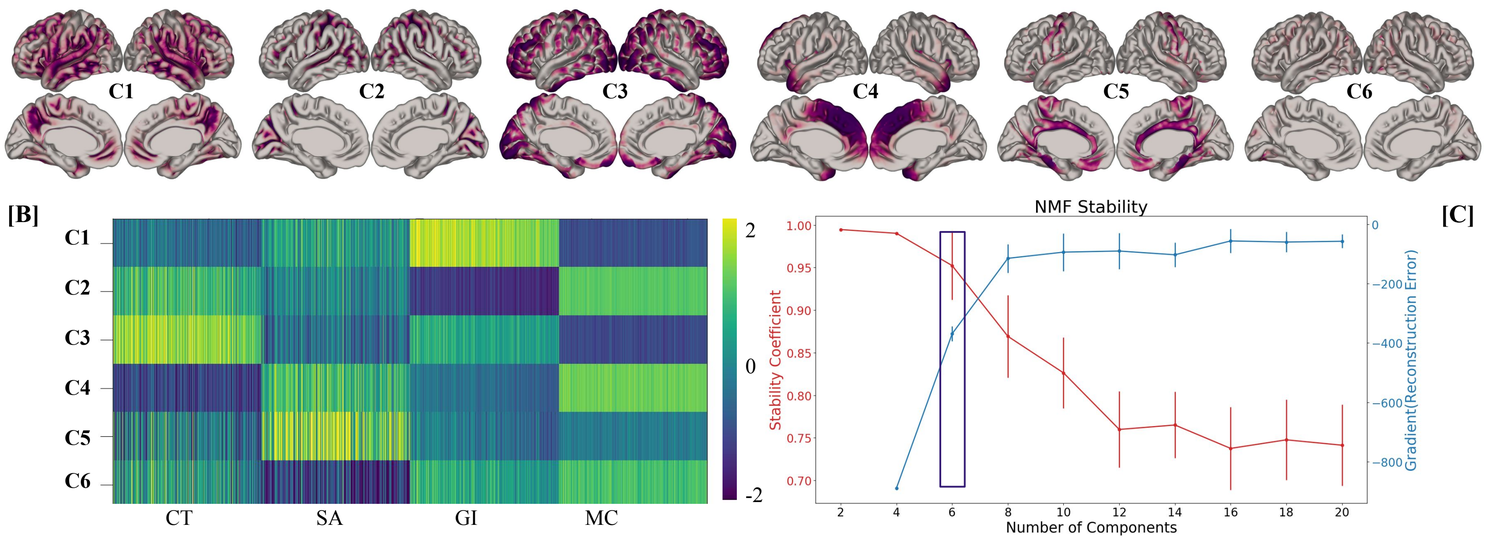

Figure.2) Spatial cortical components of a 6 component decomposition solution (top) and subjects' weights matrix [B]. Each component identifies a selection of vertices sharing a morphological variance pattern across four metrics. We identified six bilateral cortical components, showing patterns dividing the cortex into regions of associative cortices (C1), rostral and caudal poles, fusiform, lingual and cuneus gyrus (visual cortex) (C3), medial superior frontal cortex and temporal pole (C4), cingulate gyrus and somatosensory cortex (C5), frontotemporal and precunate (C1, C6).

- **OPNMF and multiple linear models results**

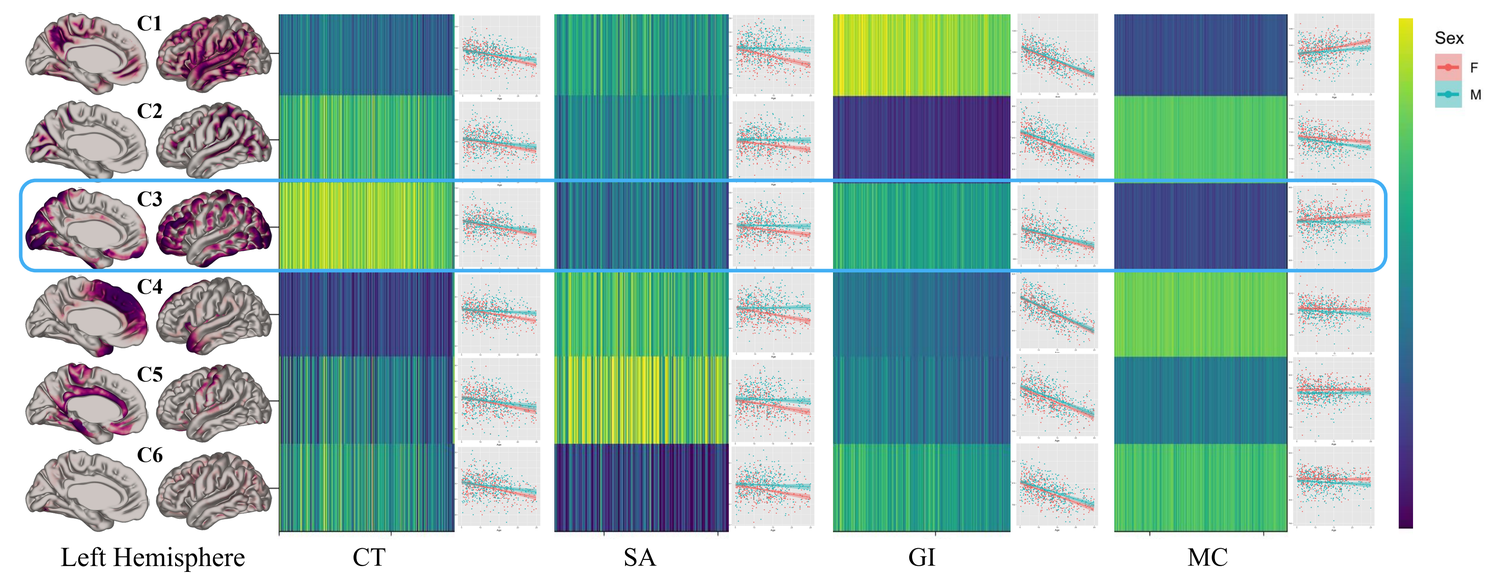

Figure.3) The components and weight matrix together show the component-specific description with respect to multiple measures in each of the spatial components. e.g., C3 corresponds more heavily to weight on a high CT, moderate SA and GI, but low MC. (in blue) Weightings of all components significantly decreased with age and were significantly greater in males compared to females across morphometric measures ($q<0.05$), except for MC components; significant age and sex interactions ($q<0.05$) were observed across SA weightings such that males show a slower SA loss relative to females.

- **PLSc results**

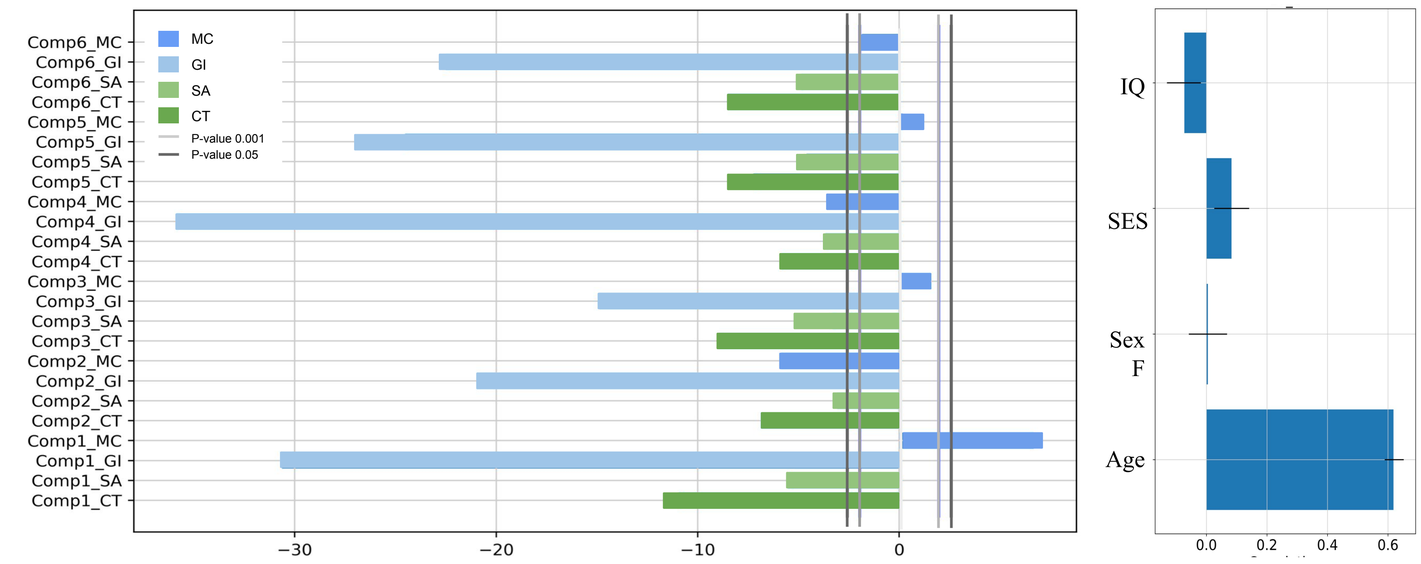

Figure.4) We identified one LV ($p<0.05$), explaining 94.6% of the covariance across cortical and demographic data. Cortical components of morphometric features (left) and demographic data (right) contributing to the LV are shown. We identified a general pattern throughout the cortex such that lower CT, SA, GI, and higher MC are correlated with older age, female sex, lower IQ, and higher SES. GI correlated with the age variable the most, negatively.

Conclusions

- We developed a technique that detects data-driven spatial patterns of covariance across the cortical sheet with respect to multiple brain features in a single framework.
- A non-uniform relationship between morphometric measures exists throughout the cortex underlying fundamental neurodevelopmental processes that covary together. Sex differences captured in most cortical regions were driven mainly by sex differences in SA covariance (rather than CT or GI) maturation.
- These components can also act as a normative scaffold for neurodevelopmental disorders.

References

1- Seidlitz et al, *Neuron*, 2018 | 2- Patel et al, *Neuroimage,* 2020 | 3- Sotiras et al, *Neuroimage*, 2015 | 4- Ad-Dabbagh et al, *Neuroimage,* 2006 | 5- Yang et al, *IEEE Transactions on Neural Networks,* 2010 | | 6- Krishnan et al, *Neuroimage*, 2011