Building brain-behavior predictions from multiple measures of fMRI connectivity dynamics

Megan Spurney[1], Joshua Faskowitz[1], Javier Gonzalez-Castillo[1], Daniel A. Handwerker[1], Peter A. Bandettini[1,2]

[1]Section on Functional Imaging Methods, National Institute of Mental Health, Bethesda, MD

[2]Functional MRI Core, National Institute of Mental Health, Bethesda, MD

Poster # 3151

INTRODUCTION

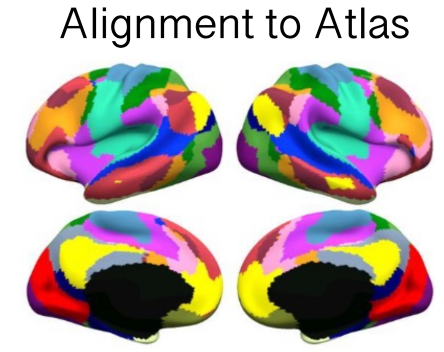
- A primary goal of neuroscience is to develop a deeper understanding of how to build predictive models to study the relationships between brain activity and behavior.
- These models are often based on resting-state fMRI data in the form of functional connectivity (FC) matrices, where each entry corresponds to the correlation between time series for a pair of regions of interest (ROIs or nodes)[1].
- This approach has been integral to key neuroimaging findings[2,3], yet it provides a limited view of the data because it focuses on time-averaged connectivity. This approach is unable to capture the dynamics of connectivity that the brain is assumed to undergo.
- Here, we explore multiple summary measures of fMRI connectivity dynamics and evaluate their predictive ability for cognitive traits such as attention and intelligence.

METHODS

971 resting-state fMRI scans[4]
(duration: 9.5 mins; Siemens 3T; TR=645ms)

fMRI Preprocessing[5] + Anatomical CompCor denoising[6]

Alignment to Atlas



Schaefer 200 cortical ROI 17 Network Atlas[7]

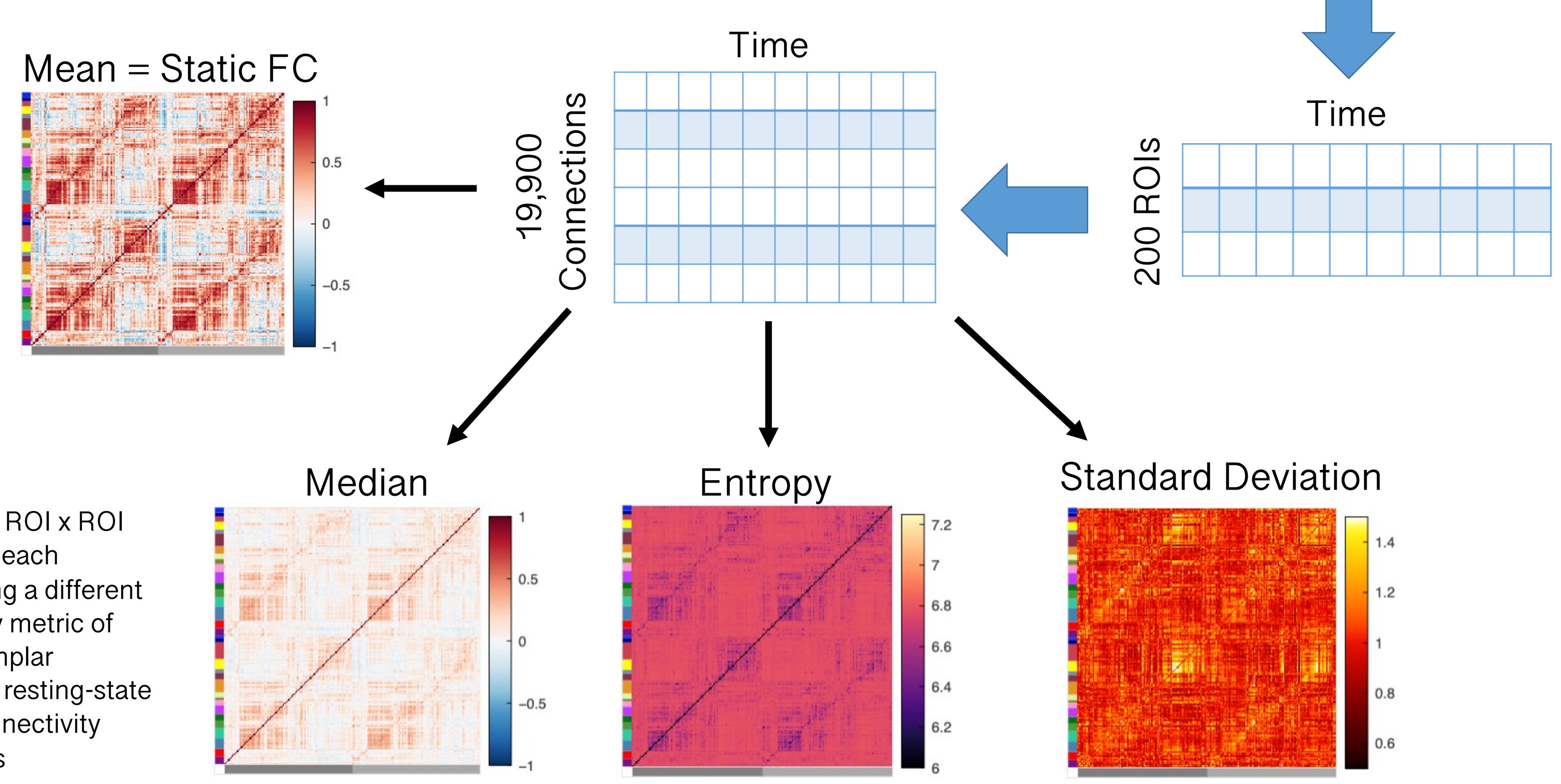


Figure 1. ROI x ROI matrices each containing a different summary metric of one exemplar subject's resting-state fMRI connectivity dynamics

Calculated multiple summary measures of fMRI connectivity dynamics for all subjects

Used these representations as inputs to a brain-behavior modeling algorithm known as Connectome-Based Predictive Modeling[8] (CPM) to predict measures of attention and intelligence

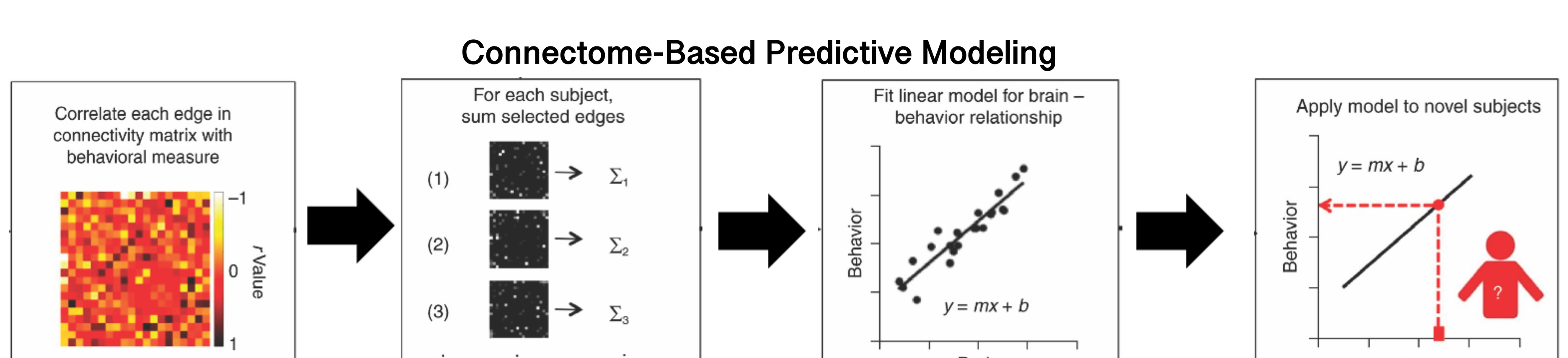


Figure 2. Description of Connectome-Based Predictive Modeling[8] (figure adapted from Shen et al. 2017)

RESULTS

- We used CPM to predict attention and intelligence scores through a 10-fold cross-validation framework using each representation of connectivity dynamics and evaluated the accuracy of the predictions by computing the Pearson's correlation between the observed and predicted values.
- We were able to significantly predict attention and intelligence scores (Figures 3a and 3b) using all four representations of brain dynamics (all parametric p-values < 0.005), but the mean (equal to functional connectivity) consistently performs the best.

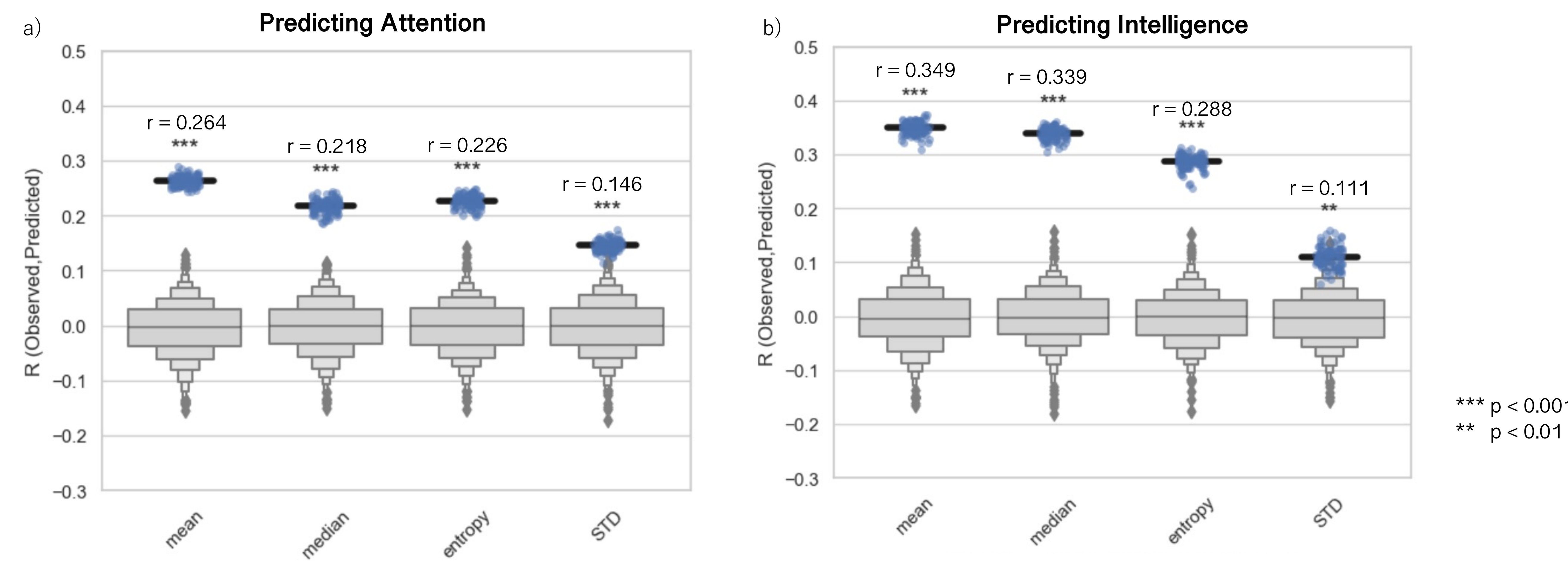
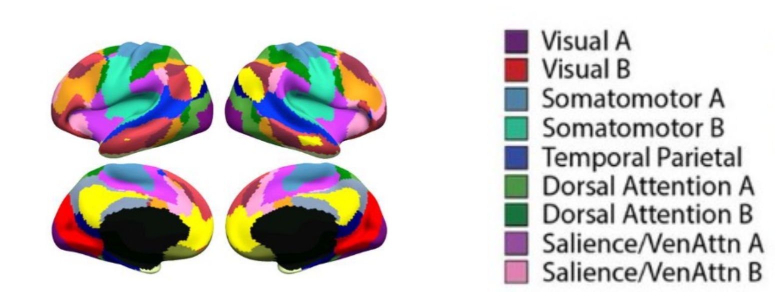


Figure 3. Results from Connectome-Based Predictive Modeling for predicting Attention Network Task scores (a) and WASI-II scores (b). Y-axis represents Pearson's R value between observed and predicted behavioral values. Blue dots show results of 100 iterations of 10-fold cross validation using true data, and gray boxen plots show distribution of results from 1,000 iterations using randomized data. Black line represents median accuracy for true models

- Figures 4a through d show the percentage of edges, grouped by functional system, that were significantly correlated with attention in the 4 models built using different representations of brain dynamics
- The amount of edges included in the model decreases significantly when we are not using the mean, which decreases interpretability of results and may decrease generalization of the models to novel data



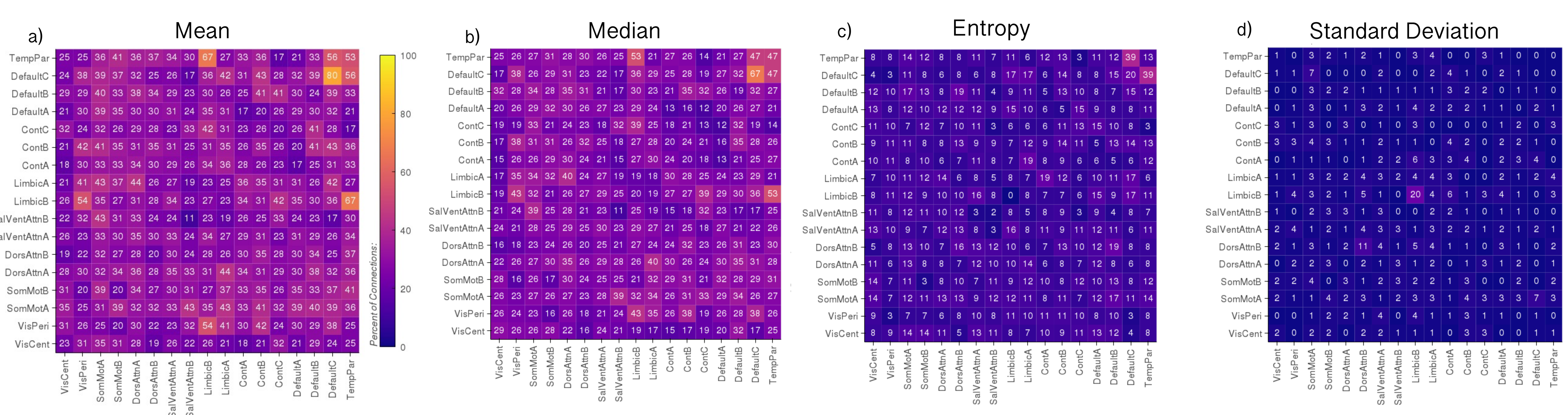


Figure 4. Results from Connectome-Based Predictive Modeling for predicting Attention Network Task. Results for predicting WASI-II showed similar trends but are not shown. Each heatmap shows the percentage of between-network edges that were included in the model built using the representation denoted in the title: a) mean b) median c) entropy d) standard deviation

CONCLUSIONS

- Our results demonstrate that average co-fluctuation, i.e., product-moment correlation, performs best as input to our predictive modeling framework.
- Future work will concentrate on if alternative time series measures, or multivariate combinations thereof, can boost brain-behavior predictive modeling from fMRI connectivity dynamics.

ACKNOWLEDGEMENTS

This research was made possible thanks to the support of the NIMH Intramural Research Program ZIA-MH002783.

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