FUNCTION FOLLOWS FORM: RELATING BRAIN ANATOMY & PHYSIOLOGY TO COGNITION & PSYCHOLOGY

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INTRODUCTION

Age has a multitude of effects on both the physiology and the functionality of the brain. In this work, we analyse data from the world's largest brain structure and activity database[1] to assess:
• the dependency structure of the dataset; and,
• the extent to which variation in brain functionality can be explained by either age, or brain anatomy and physiology.

DATA

Up to 250 separate measures are available for each subject, including demography (age, sex, etc.), mood (anxiety, depression, etc.), personality (extroversion, openness, etc.), cognition (verbal memory, reaction time, maze completion, etc.), electroencephalography (EEG; eyes-open and closed power spectra), and structural magnetic resonance imaging (MRI; gray and white matter volumes).

METHODS

• We determine the dependency structure of the dataset by estimating a probabilistic graphical model. Such models offer powerful methods for decoding the underlying conditional dependency structure in high-dimensional data.[2] We use a trans-dimensional Markov chain Monte Carlo approach based on a continuous-time birth-death process to estimate the graphical model.[3]

• We model each of the cognition variables using a subset of 60 candidate brain structure and brain activity explanatory variables. The number of included variables for each cognition variable is a function of λ, the degree to which the model is penalised for overfitting. We select the model M that minimises the generalized information criterion $GIC(M;\lambda) = 2 \times \ell(M)+\lambda$, where ℓ is the log-likelihood. We repeat this for a range of penalty values λ, subject to constraints on statistical significance.[4] We benchmark against a model that only includes age.

• To assess model stability, we bootstrap the residuals and plot the proportion of times that each candidate explanatory variable x_j is selected in each final model. The inclusion probability for x_j is estimated as[5]:

$$\frac{1}{B}\sum_{b=1}^{B} \mathbb{1}_{j\in M_\lambda^b}$$

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RESULTS

Figure 1: The posterior probabilities that each variable is codependent on each other variable, after conditioning on the remaining variables. The strongest codependencies exist between measures of a single modality, with limited codependency between cognition measures and brain activity and structure measures.

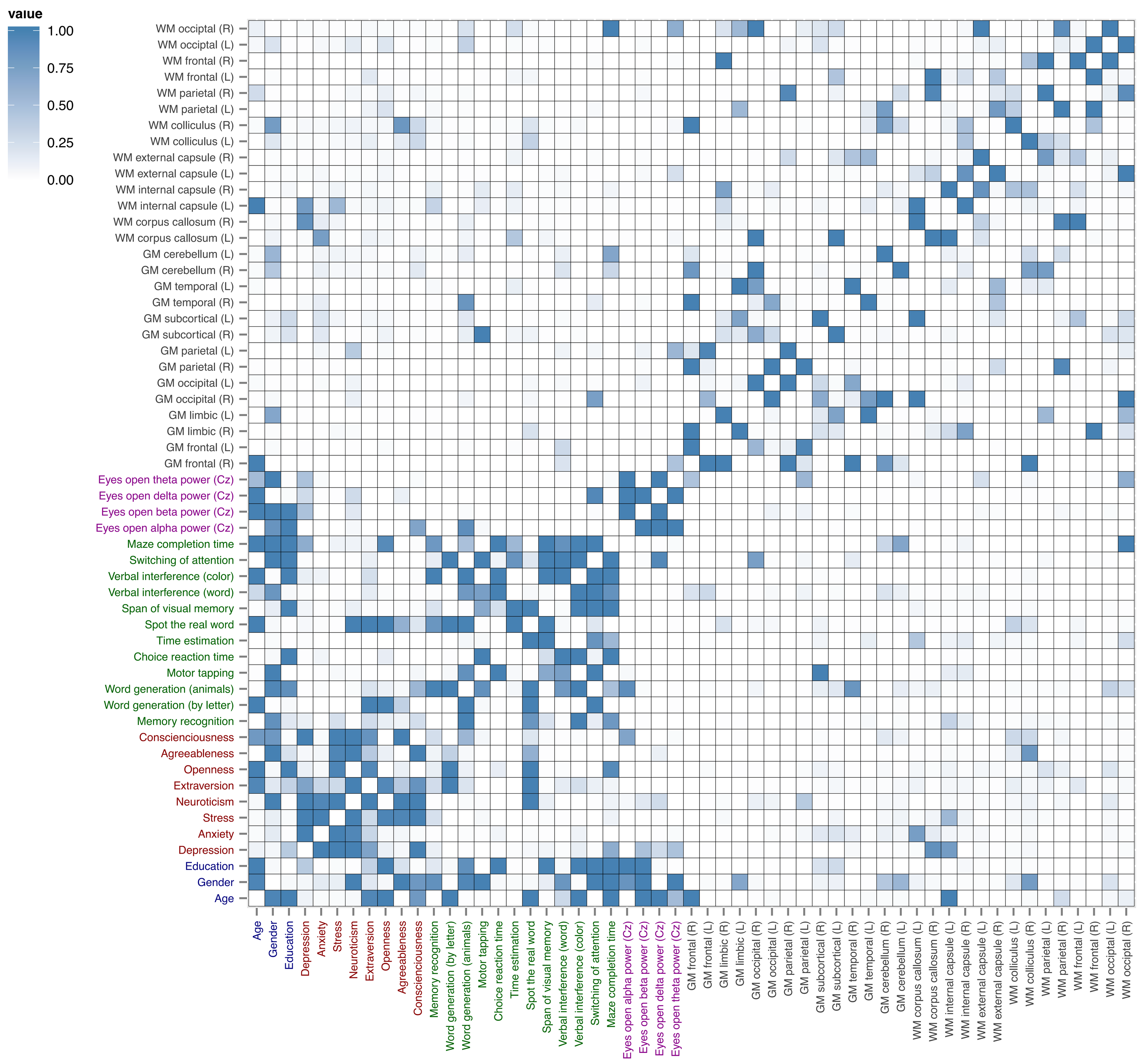

Figure 2: Bootstrapped probabilities that each candidate variable would be included in models for choice reaction time. The measures most likely to be important in explaining choice reaction time are the white matter volume in the internal capsule and the gray matter volume in the subcortical region.

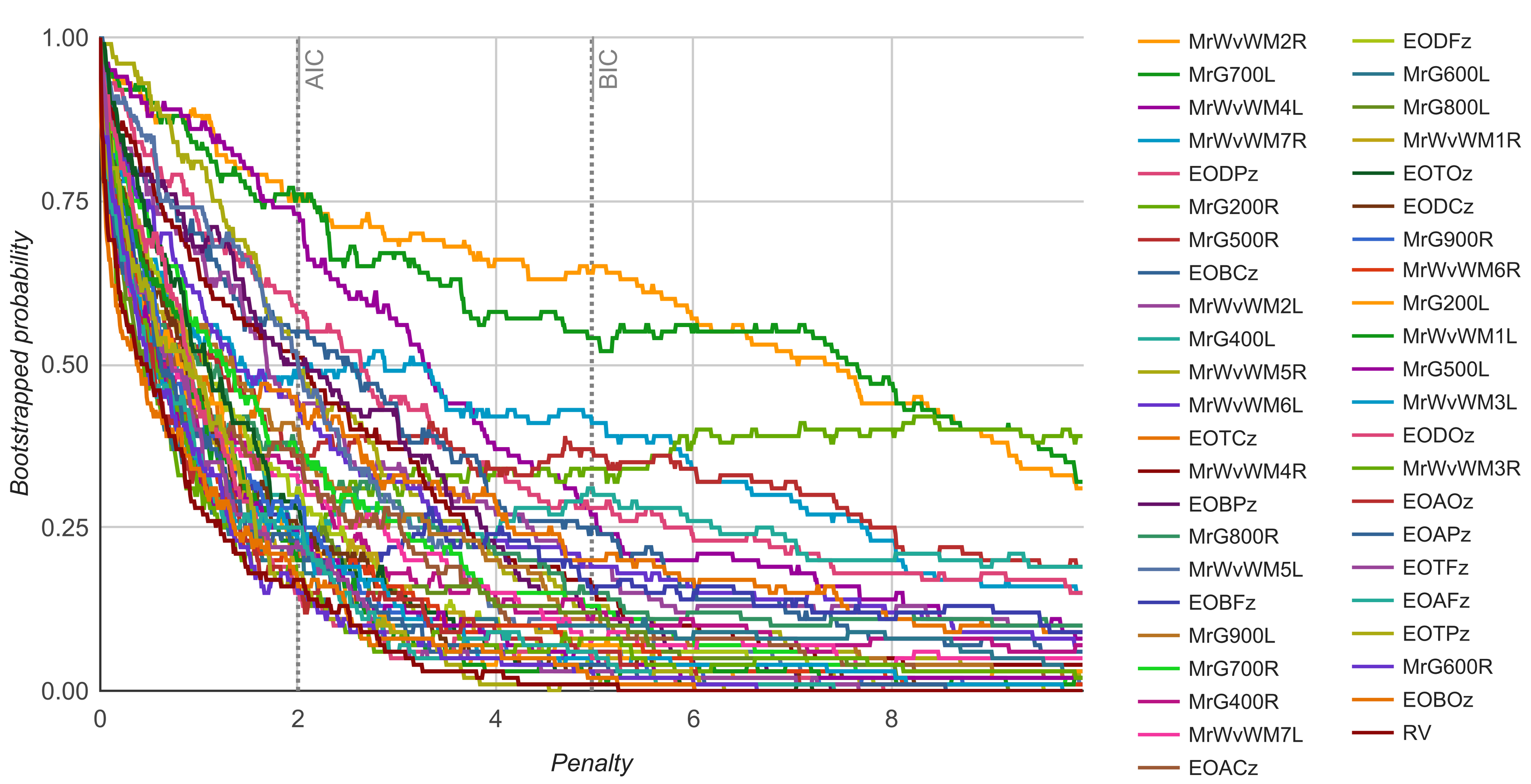

Table 1: The proportion of variance in different cognition measures explained by the proposed models. Gray matter volumes have the most explanatory power in models for maze completion time, choice reation time and emotional resilience; white matter volumes matter most for working memory capacity, negativity bias and and motor tapping; EEG matters most for memory recall and social skills.

	Maze time	Choice reaction time	Motor tapping	Working memory capacity	Memory recall	Emotional resilience	Social skills	Negativity bias
Total explained variance (R^2)								
Age	0.283	0.127	0.143	0.225	0.119	0.025	0.052	0.007
Structure & activity	0.439	0.211	0.178	0.313	0.383	0.196	0.196	0.111
EEG		0.078	0.037	0.196	0.328	0.061	0.167	0.011
MRI	0.439	0.132	0.141	0.117	0.055	0.135	0.029	0.100
Adjusted R^2								
Age	0.282	0.126	0.142	0.224	0.117	0.023	0.050	0.005
Structure & activity	0.420	0.165	0.107	0.267	0.291	0.150	0.169	0.098
Individual contributions (R^2 contribution averaged over orderings among regressors)								
Eyes open EEG		0.023	0.017	0.089	0.153	0.044	0.054	0.011
Eyes closed EEG		0.055	0.020	0.107	0.175	0.017	0.113	
Gray matter	0.374	0.079	0.035		0.055	0.078		0.038
Frontal volume (R)	0.174					0.031		
Frontal volume (L)						0.047		
Occipital (R)		0.046						
Occipital (L)		0.046						
Parietal (R)								0.038
Parietal (L)					0.029			
Subcortical (L)	0.046	0.033						
Temporal (R)					0.026			
Temporal (L)			0.020					
Cerebellum (R)			0.015					
Cerebellum (L)	0.154							
White matter	0.064	0.053	0.086	0.117		0.057	0.029	0.062
Corpus callosum (L)				0.022		0.020		
Corpus callosum (R)						0.019		
Internal capsule (R)	0.035	0.023	0.020	0.095				
External capsule (R)			0.024					
Colliculus (R)			0.026					0.017
Parietal (L)							0.029	0.015
Parietal (R)								0.030
Occipital (R)	0.029	0.030	0.016			0.018		

SUMMARY

• We elicit the dependency structure between measures of brain structure and functionality.
• We demonstrate that whilst age is the single most significant variable in terms of explaining performance in cognition tests, a combination of brain structure and activity variables is able to capture significant proportions of the variability in different measures.