

Multi-cohort cross-trait polygenic endophenotype prediction in Alzheimer's disease reveals distinct multi-level phenotypic and biomarker subtypes

CSAIL

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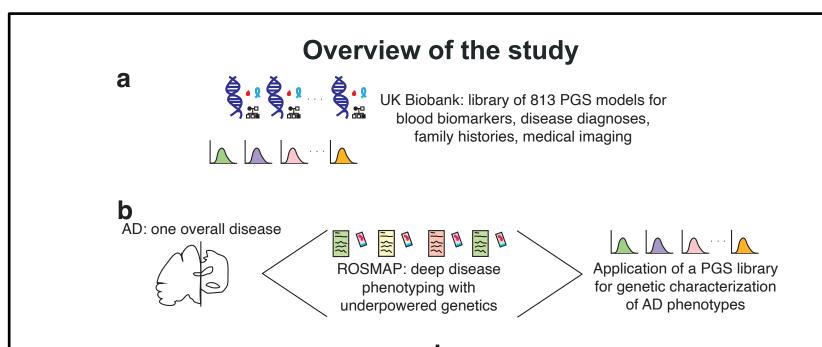


Figure 1. Study overview. (a) PGS models previously trained on the UK Biobank. **(b)** AD phenotypic heterogeneity revealed by ROSMAP.

- We integrated 713 PGS models from the UK Biobank with 37 AD clinicopathological variables derived across 1678 individuals in the ROSMAP aging cohort to study the genetics of AD phenotypic heterogeneity.
- We identified 272 FDR<0.1 associations between 37 AD phenotypes and 12 PGS. We used patterns of association to group AD phenotypes into 3 clusters for cognition, amyloid pathology, and tangles pathology.
- We show improvement of multi-PGS models over AD PGS or ApoE alone for prediction of cognition and amyloid pathology values.

Alzheimer's disease presents with rich interindividual phenotypic heterogeneity

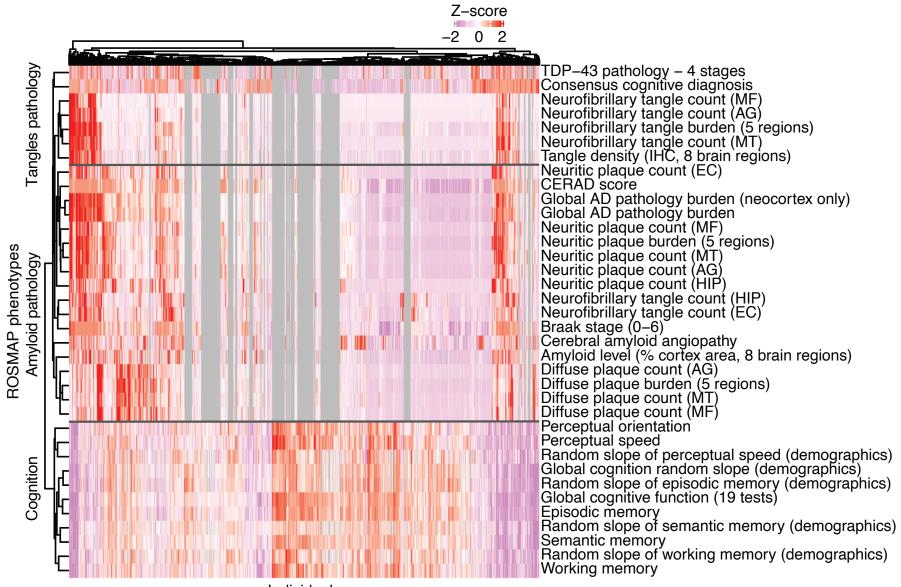
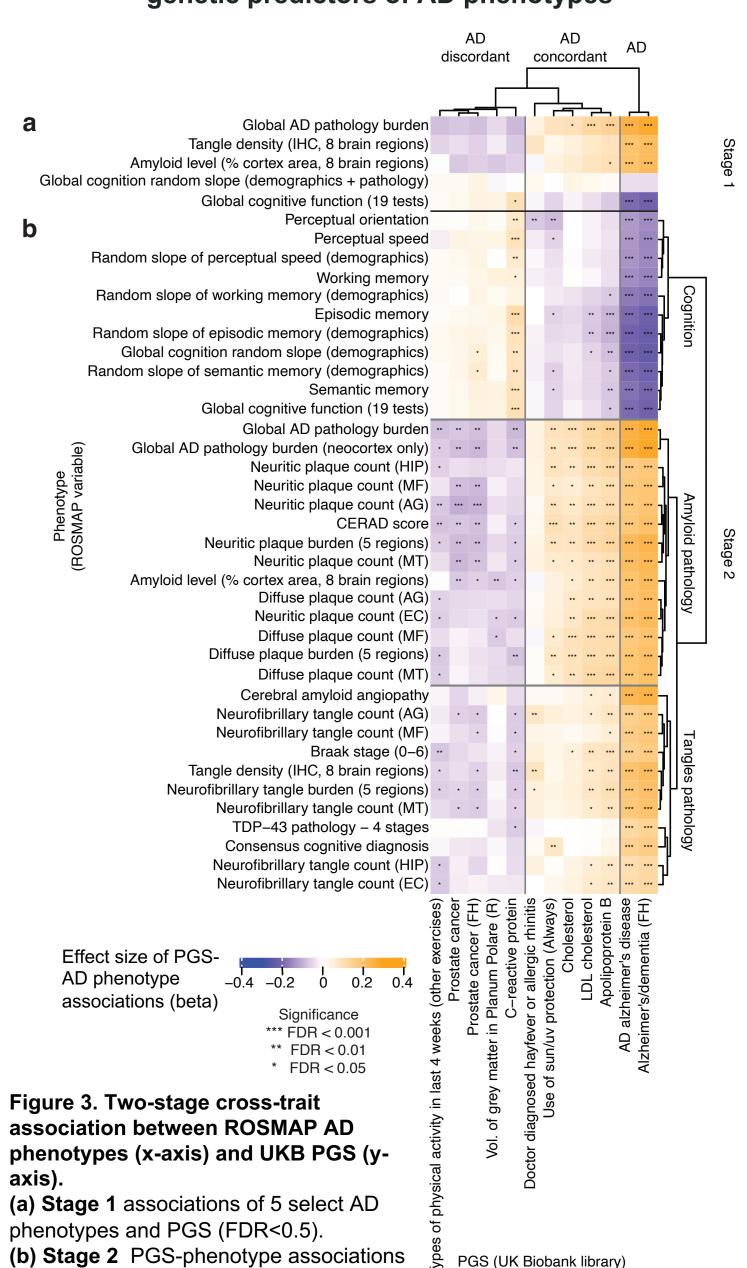


Figure 2. Phenotypic heterogeneity in the AD phenome for ROSMAP individuals. 1678 individuals, 36 AD-related clinical and pathological phenotypes, with three overarching phenotype clusters.

TDP-43, transactive response DNA binding protein 43; MF, midfrontal cortex; AG, inferior parietal cortex; MT, midtemporal cortex; IHC, immunohistochemistry; EC, entorhinal cortex; CERAD, Consortium to Establish a Registry for Alzheimer's Disease12; HIP, hippocampus; "(demographics)", variable is controlled for demographics.

Two-stage polygenic association identifies genetic predictors of AD phenotypes



between 36 AD phenotypes with 12 PGS.

We show hierarchical clustering as

dendrograms.

Multiple-PGS model enhances phenotype predictions

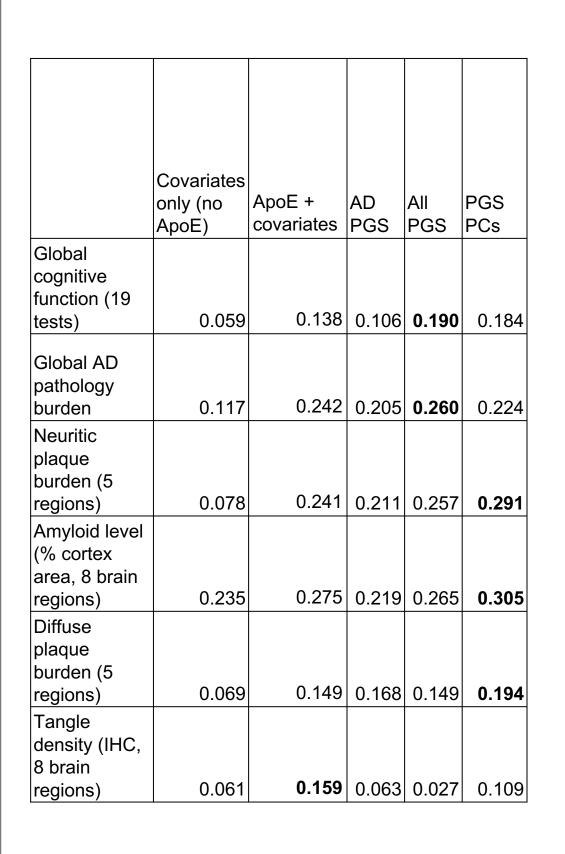


Table 1. Predictive performance of five gradient-boosted prediction models:

- . Prediction with only covariates for age, sex, population genetic principal components, and genotyping site.
- 2. Prediction with covariates and quantified apolipoprotein E genotype.
- Prediction with covariates and the PGS for AD family history.
- 4. Prediction with covariates and all 12 select AD PGS from stage 1 of the cross-trait association.
- 5. Prediction with covariates and the top 8 principal components (PCs) of the AD PGS.

Multiple-PGS prediction informs clustering of individuals

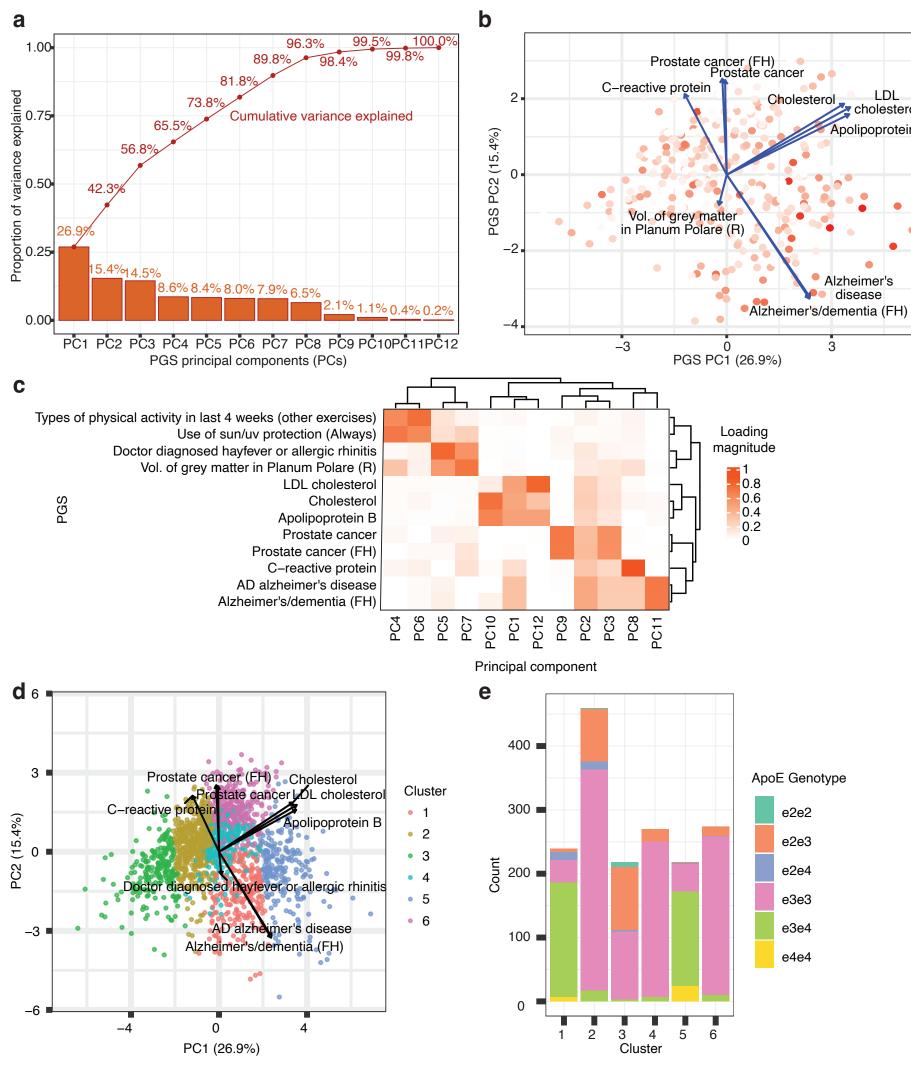


Figure 4. Individual-level clustering using principal components (PCs) derived from identified PGS.

(a) Variance explained by each PC in the principal component analysis of PGS values for ROSMAP individuals (training set).

- (b) Biplot of PCs 1 and 2 on the testing set of the predictive performance analysis, colored by neuritic plaque values. (c) The magnitudes of the PCA loadings (color) for each pair of PC (x-axis) and PGS (y-axis).
- (d) We cluster individuals by PGS PCs. We show a biplot of PCs 1 and 2 for all ROSMAP individuals, colored by cluster assignments.
- (e) We show the prevalence of each ApoE genotype within each cluster.

References and Acknowledgements

- 1. Tanigawa, Y. et al. Significant sparse polygenic risk scores across 813 traits in UK Biobank. *PLoS Genetics*. 18, e1010105 (2022).
- 2. Bellenguez, C. et al. New insights into the genetic etiology of Alzheimer's disease and related dementias. *Nature Genetics*. 54, 412–436 (2022).

Thank you to the NIH for sponsoring this work.