

Title: Neurodegeneration, Alzheimer's disease biomarkers, and longitudinal verbal learning and memory performance in late middle age.

Authors: Samantha L. Allison, PhD^{ab*}, Erin M. Jonaitis, PhD, MS^{c*}, Rebecca L. Kosciak, PhD^c, Bruce P. Hermann, PhD^c, Kimberly D. Mueller, PhD^{cd}, Robert P. Cary, BS^a, Yue Ma, PhD^a, Howard A. Rowley, PhD^{ae}, Cynthia M. Carlsson, MD^{abc}, Sanjay Asthana, MD^{ab}, Henrik Zetterberg, MD, PhD^{fghi}, Kaj Blennow, MD, PhD^{fg}, Barbara B. Bendlin, PhD^a, and Sterling C. Johnson, PhD^{abc}

*Denotes co-first authorship.

Affiliations:

^aAlzheimer's Disease Research Center, University of Wisconsin School of Medicine and Public Health, Madison, WI, USA; ^bGeriatric Research Education and Clinical Center, William S. Middleton Memorial Veterans Hospital, Madison, WI, USA; ^cWisconsin Alzheimer's Institute, University of Wisconsin School of Medicine and Public Health, Madison, WI, USA; ^dDepartment of Communication Sciences and Disorders, University of Wisconsin, Madison, WI, USA; ^eDepartment of Radiology, University of Wisconsin School of Medicine and Public Health, Madison, WI, USA; ^fDepartment of Psychiatry and Neurochemistry, Institute of Neuroscience and Physiology, the Sahlgrenska Academy at the University of Gothenburg, Mölndal, Sweden; ^gClinical Neurochemistry Laboratory, Sahlgrenska University Hospital, Mölndal, Sweden; ^hInstitute of Neurology, University College London, London, UK; ⁱUK Dementia Research Institute at UCL, London, UK

Corresponding author: Sterling C. Johnson, PhD, University of Wisconsin School of Medicine and Public Health, 600 Highland Avenue, Madison, WI, 53792, USA. Phone: 608-262-9549;

Email: scj@medicine.wisc.edu.

Abstract

This study examined the effect of neurodegeneration, and its interaction with Alzheimer's disease (AD) cerebrospinal fluid biomarkers, on longitudinal verbal learning and memory performance in cognitively unimpaired (CU) late middle-aged adults. Three hundred and forty-two CU adults (cognitive baseline mean age = 58.4), with cerebrospinal fluid and structural MRI, completed 2-10 (median = 5) cognitive assessments. Learning and memory were assessed using the Rey Auditory Verbal Learning Test (RAVLT). We used sequential comparison of nested linear mixed effects models to analyze the data. Model selection preserved a significant $\text{ptau181/A}\beta\text{42} \times \text{global atrophy} \times \text{age}$ interaction; individuals with less global atrophy and lower $\text{ptau181/A}\beta\text{42}$ levels had less learning and delayed recall decline than individuals with more global atrophy and/or higher levels of $\text{ptau181/A}\beta\text{42}$. The hippocampal volume $\times \text{age} \times \text{ptau181/A}\beta\text{42}$ interaction was not significant. Findings suggest that in a sample of CU late middle-aged adults, individuals with AD biomarkers, global atrophy, or both evidence greater verbal learning and memory decline than individuals without either risk factor.

1. Introduction

Considering that Alzheimer's disease (AD)-related pathological changes occur long before the development of clinical symptoms (Price et al., 2009; Price & Morris, 1999),

biomarkers capable of measuring AD pathophysiology *in vivo* are necessary for examining the pre-symptomatic phase of the disease. Two classes of biomarkers shown to be sensitive and specific to AD are those reflecting beta-amyloid deposition and the formation of neurofibrillary tangles (NFTs) (Betthausen et al., 2018; Betthausen et al., 2019; Brier et al., 2016; Jack et al., 2018; Klunk et al., 2004; Roe et al., 2013; Stroyk, Blennow, White, & Launer, 2003; Tapiola et al., 2009; Villemagne, Doré, Burnham, Masters, & Rowe, 2018). Several studies also focus on measures of neurodegeneration as another category of biomarkers important for defining abnormal pathophysiology across the AD spectrum, particularly during preclinical AD (Jack et al., 2018, 2016, 2015; Vos et al., 2016).

A number of methods exist for detecting neurodegeneration *in vivo*, including MRI-based morphometric estimates. In terms of the specific brain regions impacted early during the course of AD, previous cross-sectional and longitudinal structural MRI studies indicate that individuals in the preclinical phase possess greater atrophy in a number of regions, including the medial temporal lobe (e.g., entorhinal cortex and hippocampus), anterior cingulate, posterior cingulate/precuneus, and inferior parietal lobe (Chételat et al., 2012, 2010; Frisoni, Fox, Jack, Scheltens, & Thompson, 2010; Pettigrew et al., 2017; Storandt, Mintun, Head, & Morris, 2009; Susanto, Pua, & Zhou, 2015; Tondelli et al., 2012; Wang et al., 2015). There is also some evidence from cross-sectional and longitudinal research to suggest that individuals with preclinical AD have greater whole brain atrophy (Allison et al., in press; Fagan et al., 2009; Fotenos et al., 2008; Fox, Warrington, & Rossor, 1999; Schott, Bartlett, Fox, & Barnes, 2010).

Unlike biomarkers reflecting beta-amyloid deposition and the formation of NFTs, measures of brain atrophy are sensitive, but not necessarily specific to AD. For example, individuals who have suffered anoxic brain injury, those with dementia due to Lewy

bodies (DLB) or Parkinson's disease, and those with hippocampal sclerosis demonstrate hippocampal atrophy (Barber et al., 1999; Camicioli et al., 2003; Di Paola et al., 2008; Jack et al., 2002). Furthermore, schizophrenia and frontotemporal lobar degeneration are both associated with atrophy in the anterior cingulate (Baiano et al., 2007; Rosen et al., 2002), and previous research indicates that atrophy of the precuneus is found in DLB and posterior cortical atrophy (Burton et al., 2002; Lehmann et al., 2011). These findings indicate that measures of neurodegeneration may reflect neuronal loss due to a number of different etiologies, one of which may be AD. Despite this lack of specificity, prior work suggests that the use of abnormal MRI markers of neurodegeneration, in combination with biomarkers reflecting beta-amyloid deposition and NFTs, improves the prediction of future cognitive decline and progression to a clinical diagnosis of dementia due to probable AD in individuals with preclinical AD and mild cognitive impairment (MCI) at baseline (Aschenbrenner, Gordon, Benzinger, Morris, & Hassenstab, 2018; Bouwman et al., 2007; Davatzikos, Bhatt, Shaw, Batmanghelich, & Trojanowski, 2011; Jack et al., 2017; Soldan et al., 2019; van Maurik et al., 2017; van Rossum et al., 2012; Vemuri et al., 2009). These results highlight the need to incorporate measures of neurodegeneration when examining cognitive decline in preclinical and prodromal AD.

Previous work by our group suggests that individuals with preclinical AD demonstrate greater verbal learning and memory decline than late middle-aged adults without evidence of AD pathophysiology (defined using biomarkers of beta-amyloid deposition) (Clark et al., 2018); however, less is known about the relationship between measures of neurodegeneration and verbal learning and memory decline in this group. Therefore, the purpose of this study was to examine the effect of neurodegeneration, and its interaction with AD pathophysiology as indexed by CSF biomarkers, on longitudinal verbal learning and memory performance in late middle age.

We defined neurodegeneration using estimates of hippocampal volume and global atrophy based on recent work by our group suggesting that these two MRI-based metrics are automated, robust, and computationally efficient for defining neurodegeneration across the AD continuum (Allison et al., 2019). We hypothesized that hippocampal and global atrophy would be related to declines in both verbal learning and memory performance, and that individuals with atrophy on structural MRI and abnormal AD biomarkers (low CSF levels of $A\beta_{42}/A\beta_{40}$, high levels of $p\tau_{181}/A\beta_{42}$ or $p\tau_{181}$) would evidence the greatest amount of decline on these cognitive measures.

2. Methods

2.1 Participants.

Participants included 342 late middle-aged and older adults (see Table 1 for demographic information) from the Wisconsin Registry for Alzheimer's disease Prevention (WRAP) or the Wisconsin Alzheimer's Disease Research Center (WADRC). These cohorts consist of participants enriched with a parental family history of AD (Johnson et al., 2018). Participants from WRAP and WADRC complete a baseline cognitive assessment. For the WRAP participants, a second cognitive assessment occurs four years after the baseline evaluation, and then subsequent visits occur every two years. The WADRC participants complete annual or biennial cognitive assessments. Participants in the current study completed a median of 5 (range=2-10) cognitive assessments.

To qualify for the current analysis, participants needed to have at least one structural MRI scan and one visit in which CSF levels of $p\tau_{181}$, $A\beta_{42}$, and $A\beta_{40}$ were collected within 1.5 years of each other. All participants also needed to be classified as cognitively unimpaired at baseline (i.e., no clinical diagnosis of dementia or MCI) based on the National Institute on Aging-Alzheimer's Association's consensus conference criteria (Albert et al., 2011; McKhann et al.,

2011) by a team of clinicians (neuropsychologists, physician dementia specialists, and nurse practitioners) blind to biomarker data (e.g., PET or CSF data). Exclusion criteria included completion of only one study visit, as well as a history of neurological conditions (e.g., multiple sclerosis, stroke/TIA, Parkinson's disease, epilepsy) or a significant psychiatric condition (e.g., bipolar disorder or schizophrenia). The inclusion of human participants was supported by the University of Wisconsin-Madison Institutional Review Board. All participants provided informed consent for this study.

2.2 Structural MRI.

MRI images were acquired in one scanning session using two identical GE 3.0 Tesla MR750 scanners (Waukesha, WI, USA) with an 8-channel head coil (Excite HD Brain Coil; GE Healthcare). T1-weighted brain volumes were acquired in the axial plane with a 3-D inversion-recovery prepared fast spoiled gradient-echo sequence using the following parameters: inversion time (TI) = 450 ms; repetition time (TR) = 8.2 ms; echo time (TE) = 3.2 ms; flip angle = 12°; acquisition matrix = 256 × 256 × 156 mm; field of view (FOV) = 256 mm; slice thickness = 1.0 mm. Additionally, 14 subjects were scanned with the same parameters, except TR = 8.1 ms. Finally, 1 subject was scanned with a shorter sequence that was less susceptible to motion artifacts, after it was determined their first scan would likely be unusable. The shorter sequence parameters were: TI = 450 ms; TR = 6.0 ms; TE = 2.2 ms; flip angle = 12°; acquisition matrix = 256 × 256 × 130 mm; FOV = 256 mm; slice thickness = 1.2 mm. Cushions helped reduce head movement during scanning. A radiologist (H.A.R.) reviewed all scans for abnormalities.

Measures of neurodegeneration included global brain atrophy and hippocampal volume. An estimate of global brain atrophy (i.e., CSF/(total gray + total white matter volumes)) was derived from the T1-weighted IRSPGR sequence by segmenting tissue types into CSF, as well as

gray and white matter volumes, using SPM12 (www.fil.ion.ucl.ac.uk/spm). Hippocampal volume was calculated using FSL-FIRST (Patenaude, Smith, Kennedy, & Jenkinson, 2011), and corrected for intracranial volume (ICV) derived using the reverse brain mask method in SPM12 (i.e., hippocampal volume/ICV) (Keihaninejad et al., 2010). One image failed based on visual inspection of the images by S.L.A. Structural MRI data were collected, on average, 3.28 years (SD=3.67 years) from the baseline cognitive assessment. Other information about the relative timing of the assessments is located in Table 1.

2.3 Cerebrospinal fluid levels of Alzheimer's disease biomarkers.

CSF levels of A β ₄₂ and ptau₁₈₁ were obtained via a lumbar puncture in which twenty-two mL of CSF were removed from the L3-L4 or L4-L5 vertebral interspace. CSF samples (sent in batches at two time points) were analyzed at the Clinical Neurochemistry Laboratory at the Sahlgrenska Academy of the University of Gothenburg, Sweden using commercially available enzyme-linked immunosorbent assay methods (INNOTEST assays, Fujirebio, Ghent, Belgium; Triplex assays, MSD Human A β peptide ultra-sensitive kit, Meso Scale Discovery, Gaithersburg, MD). CSF samples were assayed for A β ₄₂ and ptau₁₈₁. Because of widely reported batch effects in analysis of CSF data (CITE), analyte values from the second batch were converted to the space of the first batch based on generalized linear models. Details of this modeling process are reported elsewhere (CITE).

2.4 Cognitive assessment.

We utilized the learning and delayed recall phases from the Rey Auditory Verbal Learning Test (RAVLT) (Rey, 1941) on the basis of prior meta-analyses demonstrating a significant relationship between measures of learning and memory and AD biomarkers (Bäckman, Jones, Berger, Laukka, & Small, 2005; Baker et al., 2017; Han, Nguyen, Stricker, &

Nation, 2017; Hedden, Oh, Younger, & Patel, 2013), along with the fact that these measures were available at all study visits for both the WRAP and WADRC participants. Learning performance was defined as the number of words recalled across trials 1-5 (Total: 0-75). Delayed recall performance was defined as the number of words recalled after a thirty-minute delay (Total: 0-15).

2.5 Statistical analyses.

Statistical analyses were conducted in R version 3.4.4 (R Core Team, 2017) using the lmerTest package (Kuznetsova, Brockhoff, & Christensen, 2017), which uses the Satterthwaite approximation to compute degrees of freedom. We used sequential comparison of nested linear mixed effects models to test our hypotheses that hippocampal or global atrophy would be related to declines in RAVLT learning and memory outcomes, and that those with atrophy on structural MRI and abnormal CSF biomarkers would evidence the greatest RAVLT declines. Maximum likelihood estimation was used for model fitting. The predictors (i.e., neurodegeneration measures and CSF biomarkers) were standardized (unadjusted z-scored) prior to conducting analyses. Higher CSF levels of ptau₁₈₁/Aβ₄₂ reflect a greater degree of AD-related pathophysiology, whereas higher global atrophy and smaller hippocampi are indicative of structural changes linked to aging and disease (Jack et al., 2018). For each outcome (RAVLT verbal learning or delayed recall), the full model included: random intercept and age-related slopes; fixed effects covariates of sex, years of education, and prior exposure to the cognitive battery (“practice”, visit number – 1, coded categorically); and hypothesis-related fixed effects of interest including age (centered at the mean baseline age), ptau₁₈₁/Aβ₄₂, hippocampal volume, global atrophy, and interactions between ptau₁₈₁/Aβ₄₂, each brain measure, and age. A preliminary analysis treated outcome (learning vs recall) as a fourth interacting variable to test

whether the effects of any predictors differed meaningfully between the two outcomes; following a significant four-way interaction between outcome variable, $\text{ptau}_{181}/\text{A}\beta_{42}$, hippocampal volume, and age, the two were outcomes separately (Supplementary Table S1). The four-way interaction was not significant for global atrophy.

Model selection was performed as follows. First, the relative contribution of age and practice on longitudinal trajectories was considered by comparing four simple models: linear age, no practice; quadratic age, no practice; linear age plus practice; and quadratic age plus practice. After this, the effects of the predictors of interest were examined by comparing a fully saturated model to smaller nested models on the basis of Akaike's information criterion (AIC), and in the case of ties, the Bayesian information criterion (Schwarz, 1978). The saturated model (with all interactions of interest) was run first and compared to a model with all of the two-way interactions. If the smaller model improved the fit, two-way interaction terms were removed by order of decreasing p-value until removing further terms did not improve model fit. All main effect terms were retained. If the AICs were the same for the compared models, the model with the lower Bayesian information criterion was selected (BIC).

2.5.2 Hypothesis tests. Reported p-values represent nominal probability under the null hypothesis. No adjustments were made for multiplicity due to model selection or incorporation of reviewer-suggested changes.

3. Results

3.1 Primary analysis: The effects of CSF $\text{ptau}_{181}/\text{A}\beta_{42}$, global atrophy, and hippocampal volume on RAVLT learning and delayed recall. The initial mixed effects model treating cognitive outcome as a fixed effect resulted in a significant four-way interaction, indicating that the three-way interaction between $\text{ptau}_{181}/\text{A}\beta_{42}$, hippocampal volume, and age differed for the

learning and delayed recall outcomes. Model fit statistics are displayed in Table 2. Therefore, follow-up models were fit separately for these two outcomes.

3.1.1. RAVLT Learning: Model selection preserved a significant $\text{ptau}_{181}/\text{A}\beta_{42} \times \text{global atrophy} \times \text{age}$ interaction, indicating that age trajectories in RAVLT learning depended both on CSF markers of AD and on global atrophy. A significant hippocampal volume \times age interaction was also retained. Simple slopes for three levels each of global atrophy (columns), hippocampal volume (rows), and $\text{ptau}_{181}/\text{A}\beta_{42}$ (lines) are plotted in Figure 1. Briefly, the deleterious effect of $\text{ptau}_{181}/\text{A}\beta_{42}$ is most pronounced in those with larger global brain volumes (i.e., lower levels of global atrophy; left column of panels), whereas those with higher levels of atrophy evidence similar decline regardless of $\text{ptau}_{181}/\text{A}\beta_{42}$. Those with larger hippocampal volumes (bottom row of panels) showed slightly less steep age-related cognitive decline than those with smaller hippocampal volumes (top row of panels). Model parameters and fit statistics are displayed in Table 3A-B.

3.1.2. RAVLT Delayed Recall: In the initial model fit, the two highest-order interactions had p-values $< .10$; therefore, no further selection was performed. Results suggested both a significant $\text{ptau}_{181}/\text{A}\beta_{42} \times \text{global atrophy} \times \text{age}$ interaction, indicating that age trajectories in RAVLT delayed recall depended both on CSF markers of AD and on global atrophy, and a nonsignificant $\text{ptau}_{181}/\text{A}\beta_{42} \times \text{hippocampal volume} \times \text{age}$ interaction, indicating a weaker dependence between these variables. Simple slopes for three levels each of global atrophy (columns), hippocampal volume (rows), and $\text{ptau}_{181}/\text{A}\beta_{42}$ (lines) are plotted in Figure 1. Briefly, the deleterious effect of $\text{ptau}_{181}/\text{A}\beta_{42}$ is most pronounced in those with lower levels of global atrophy (left column of panels), and to a weaker degree, those with smaller hippocampal volumes (top row of panels). Model parameters are displayed in Table 4.

4. Discussion

The current study examined the effect of neurodegeneration (as assessed with volumetric indices of hippocampal volume and global atrophy) and its interaction with CSF AD biomarkers on longitudinal verbal learning and memory performance in late middle age. Previous research by our group indicates that CU late middle-aged individuals with evidence of beta-amyloid deposition (defined using available PET and/or CSF data) exhibit greater rates of decline on tasks of verbal learning and memory than their counterparts without biomarker evidence of AD (Clark et al., 2018), which is consistent with the larger literature examining these relationships in older adults (Bäckman et al., 2005; Baker et al., 2017; Han et al., 2017; Hedden et al., 2013). Of note, our prior study found that amyloid deposition was associated with greater rates of cognitive decline regardless of whether individuals also had elevated levels of CSF tau.

The present study adds to our prior work by demonstrating that the deleterious effects of AD-related pathophysiology (i.e., higher levels of CSF ptau₁₈₁/Aβ₄₂) on verbal learning and memory performance depend on the degree of global atrophy present. More specifically, individuals with a greater degree of global atrophy evidenced similar rates of decline regardless of the degree of AD pathophysiology present. In contrast, in individuals with larger global brain volumes, the presence of preclinical Alzheimer's disease was associated with steeper declines in verbal learning and memory. These findings suggest that the presence of AD biomarkers, global atrophy, or both global atrophy and AD biomarkers are all associated with greater verbal learning and memory decline in a sample of late middle-aged adults.

In contrast to the global atrophy findings, the ptau₁₈₁/Aβ₄₂ × hippocampal volume × age interaction was not a significant predictor of either outcome, although it was retained in the model of delayed recall ($p < .10$). This discrepancy may be due to methodological reasons. More

specifically, in contrast to global atrophy, the estimation of hippocampal volume requires differentiation of gray from white matter structures. This difference may result in less accurate estimates for hippocampal volumes than those obtained for global atrophy measures, which do not necessitate segmentation of white from gray matter volumes (Fischl et al., 2002). This is particularly relevant when examining a population consisting of late middle-aged and older adults given that white matter signal intensity declines with age (Salat et al., 2009). This difference in reliability may have accounted for the discrepant findings for hippocampal volume vs global atrophy in the current investigation.

Another reason for the discrepant findings in the current study may be that global atrophy is a better metric of brain reserve than hippocampal volume. The concept behind brain reserve suggests that some individuals evidence less cognitive decline than their peers, and that this may be due to differences in brain structure or function (Stern, 2018). Previous investigations have used a number of neuroimaging methods for defining brain reserve, including cortical thickness, gray matter volume, white matter hyperintensity burden, resting cerebral blood flow, as well as both total brain volume and hippocampal volume (for reviews on both cognitive reserve and brain reserve, see: Fratiglioni & Wang, 2007; Stern, 2018). A measure of global atrophy may be more reflective of neuronal loss due to a number of different etiologies, whereas hippocampal volume loss may be more related to changes due to AD (e.g., Henneman et al., 2009; Jack et al., 2000). Additional research is needed, but this may have accounted for the fact that only individuals with less global atrophy and lower levels of AD biomarkers demonstrated less steep decline over time on measures of verbal learning and memory in the current study.

The findings from the current study are similar to previous research in that we too observed a three-way interaction (i.e., neurodegeneration x AD biomarker x age); however, the

existing literature has found that the greatest degree of decline in cognition is observed in individuals with both atrophy and the presence of AD pathophysiology (Aschenbrenner et al., 2018; Bilgel et al., 2018; Mormino et al., 2014; Soldan et al., 2016). In contrast, the present work found that AD biomarkers interacted with a measure of global atrophy such that trajectories were fairly similar in those carrying at least one of these risk factors (i.e., global atrophy, presence of AD biomarkers, or both global atrophy and AD biomarkers), whereas less verbal learning and memory decline was evident in those with both normal AD biomarker levels and larger brain volumes. The average age of participants in these past investigations was at least 70 years old at baseline (Aschenbrenner et al., 2018; Bilgel et al., 2018; Mormino et al., 2014), with the exception that the Soldan et al. (2016) subsample with the presence of both neurodegeneration and AD biomarkers was 64. In contrast, the average baseline age in the current study was 58. This difference in age may have accounted for the discrepant findings.

Our conclusions here should be considered in light of a few design limitations. First, our analyses were limited to a single episodic learning and memory neuropsychological test because of the in-common availability of the RAVLT. To limit the analytical complexity of our analyses, as well as the inferential problems associated with multiple testing (Gelman & Geurts, 2017), we also considered only a subset of the possible measures of neurodegeneration (Frisoni et al., 2010) and CSF biomarkers (Merluzzi et al., 2019; Olsson et al., 2016). Future analyses in other cohorts should examine the conceptual replicability of these findings using different measures. The homogeneity of the sample is also a weakness, as both cohorts consisted largely of late middle-aged adults with a relatively high level of education (average of 16 years). Our center is currently recruiting a more diverse sample to establish the robustness of our findings to differences in demographic background.

Conclusions. This study joins a growing body of research that is empirically characterizing the pre-symptomatic biomarker profile in AD. Our results suggest that AD biomarkers are associated with verbal learning and memory decline, and that the impact of AD biomarkers on verbal learning and memory performance is greatest in those with larger total brain volumes. Future research would benefit from following this cohort overtime, as well as examining the interaction between additional measures of neurodegeneration (e.g., CSF NfL or neurogranin) and AD pathophysiology (e.g., PET measures of beta-amyloid and neurofibrillary tangles) on cognitive performance, defined using verbal learning and memory measures, as well as measures of other cognitive functions (e.g., executive function).

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7. References

- Akaike, H. (1987). Factor analysis and AIC. In *Selected Papers of Hirotugu Akaike* (pp. 371–386). Springer.
- Albert, M. S., DeKosky, S. T., Dickson, D., Dubois, B., Feldman, H. H., Fox, N. C., ... Petersen, R. C. (2011). The diagnosis of mild cognitive impairment due to Alzheimer's disease: Recommendations from the National Institute on Aging-Alzheimer's Association workgroups on diagnostic guidelines for Alzheimer's disease. *Alzheimer's & Dementia*, 7(3), 270–279.

Allison, S. L., Kosciak, R. L., Cary, P., Jonaitis, E. M., Chin, N., Rowley, H. A., Zetterberg, H., Blennow, K., Carlsson, C. M., Asthana, S., Bendlin, B. B., & Johnson, S. C. (2019). Comparison of different MRI-based morphometric estimates for defining neurodegeneration across the Alzheimer's disease spectrum. *NeuroImage: Clinical*.

Aschenbrenner, A. J., Gordon, B. A., Benzinger, T. L., Morris, J. C., & Hassenstab, J. J. (2018). Influence of tau PET, amyloid PET, and hippocampal volume on cognition in Alzheimer disease. *Neurology*, 10.1212/WNL.0000000000006075.

Bäckman, L., Jones, S., Berger, A.-K., Laukka, E. J., & Small, B. J. (2005). Cognitive impairment in preclinical Alzheimer's disease: A meta-analysis. *Neuropsychology*, 19(4), 520.

Baiano, M., David, A., Versace, A., Churchill, R., Balestrieri, M., & Brambilla, P. (2007). Anterior cingulate volumes in schizophrenia: a systematic review and a meta-analysis of MRI studies. *Schizophrenia Research*, 93(1), 1–12.

Baker, J. E., Lim, Y. Y., Pietrzak, R. H., Hassenstab, J., Snyder, P. J., Masters, C. L., & Maruff, P. (2017). Cognitive impairment and decline in cognitively normal older adults with high amyloid- β : A meta-analysis. *Alzheimer's & Dementia: Diagnosis, Assessment & Disease Monitoring*, 6, 108–121.

Barber, R., Gholkar, A., Scheltens, P., Ballard, C., McKeith, I. G., & O'Brien, J. T. (1999). Medial temporal lobe atrophy on MRI in dementia with Lewy bodies. *Neurology*, 52(6), 1153–1153.

Berenguer, R. G., Argilés, J. A. M., Ruiz, C. M., Payá, J. S., Cantó, M. A. B., & Santana, C. L. (2014). Alzheimer disease cerebrospinal fluid biomarkers predict cognitive decline in healthy elderly over 2 years. *Alzheimer Disease & Associated Disorders*, 28(3), 234–238.

Bethausen, T., Cody, K., Zammit, M., DeFilippo, A., Murali, D., Barnhart, T., ... Christian, B. (2018). [18F] MK-6240 PET quantification and image feature characterization from controls to Alzheimer's disease. *Journal of Nuclear Medicine*, 59(supplement 1), 82–82.

Bethausen, T. J., Cody, K. A., Zammit, M. D., Murali, D., Converse, A. K., Barnhart, T. E., ... Christian, B. T. (2019). In Vivo Characterization and Quantification of Neurofibrillary Tau PET Radioligand 18F-MK-6240 in Humans from Alzheimer Disease Dementia to Young Controls. *Journal of Nuclear Medicine*, 60(1), 93–99.

Bilgel, M., An, Y., Hefphrey, J., Elkins, W., Gomez, G., Wong, D. F., ... Resnick, S. M. (2018). Effects of amyloid pathology and neurodegeneration on cognitive change in cognitively normal adults. *Brain*, 141(8), 2475–2485.

Bouwman, F. H., Schoonenboom, S. N. M., van Der Flier, W. M., Van Elk, E. J., Kok, A., Barkhof, F., ... Scheltens, P. (2007). CSF biomarkers and medial temporal lobe atrophy predict dementia in mild cognitive impairment. *Neurobiology of Aging*, 28(7), 1070–1074.

- Brier, M. R., Gordon, B., Friedrichsen, K., McCarthy, J., Stern, A., Christensen, J., ... Hassenstab, J. (2016). Tau and A β imaging, CSF measures, and cognition in Alzheimer's disease. *Science Translational Medicine*, 8(338), 338ra66-338ra66.
- Burton, E. J., Karas, G., Paling, S. M., Barber, R., Williams, E. D., Ballard, C. G., ... O'Brien, J. T. (2002). Patterns of cerebral atrophy in dementia with Lewy bodies using voxel-based morphometry. *Neuroimage*, 17(2), 618-630.
- Camicioli, R., Moore, M. M., Kinney, A., Corbridge, E., Glassberg, K., & Kaye, J. A. (2003). Parkinson's disease is associated with hippocampal atrophy. *Movement Disorders*, 18(7), 784-790.
- Chételat, Gaël, Villemagne, V. L., Bourgeat, P., Pike, K. E., Jones, G., Ames, D., ... O'Keefe, G. J. (2010). Relationship between atrophy and β -amyloid deposition in Alzheimer disease. *Annals of Neurology*, 67(3), 317-324.
- Chételat, Gael, Villemagne, V. L., Villain, N., Jones, G., Ellis, K. A., Ames, D., ... Rowe, C. C. (2012). Accelerated cortical atrophy in cognitively normal elderly with high β -amyloid deposition. *Neurology*, 78(7), 477-484.
- Clark, L. R., Berman, S. E., Norton, D., Kosciak, R. L., Jonaitis, E., Blennow, K., ... Zetterberg, H. (2018). Age-accelerated cognitive decline in asymptomatic adults with CSF β -amyloid. *Neurology*, 10.1212/WNL.0000000000005291.
- Davatzikos, C., Bhatt, P., Shaw, L. M., Batmanghelich, K. N., & Trojanowski, J. Q. (2011). Prediction of MCI to AD conversion, via MRI, CSF biomarkers, and pattern classification. *Neurobiology of Aging*, 32(12), 2322. e19-2322. e27.
- Di Paola, M., Caltagirone, C., Fadda, L., Sabatini, U., Serra, L., & Carlesimo, G. A. (2008). Hippocampal atrophy is the critical brain change in patients with hypoxic amnesia. *Hippocampus*, 18(7), 719-728.
- Fagan, A. M., Head, D., Shah, A. R., Marcus, D., Mintun, M., Morris, J. C., & Holtzman, D. M. (2009). Decreased cerebrospinal fluid A β 42 correlates with brain atrophy in cognitively normal elderly. *Annals of Neurology*, 65(2), 176-183.
- Fischl, B., Salat, D. H., Busa, E., Albert, M., Dieterich, M., Haselgrove, C., ... & Dale, A.M. (2002). Whole brain segmentation: Automated labeling of neuroanatomical structures in the human brain. *Neuron*, 33(3), 341-355.
- Fotenos, A. F., Mintun, M. A., Snyder, A. Z., Morris, J. C., & Buckner, R. L. (2008). Brain volume decline in aging: Evidence for a relation between socioeconomic status, preclinical Alzheimer disease, and reserve. *Archives of Neurology*, 65(1), 113-120.
- Fox, N. C., Warrington, E. K., & Rossor, M. N. (1999). Serial magnetic resonance imaging of cerebral atrophy in preclinical Alzheimer's disease. *The Lancet*, 353(9170), 2125.

Fratiglioni, L., & Wang, H. X. (2007). Brain reserve hypothesis in dementia. *Journal of Alzheimer's Disease*, *12*(1), 11-22. Review.

Frisoni, G. B., Fox, N. C., Jack, C. R., Scheltens, P., & Thompson, P. M. (2010). The clinical use of structural MRI in Alzheimer disease. *Nature Reviews Neurology*, *6*(2), 67–77.

Gelman, A., & Geurts, H. M. (2017). The statistical crisis in science: How is it relevant to clinical neuropsychology? *The Clinical Neuropsychologist*, *31*(6–7), 1000–1014.

Han, S. D., Nguyen, C. P., Stricker, N. H., & Nation, D. A. (2017). Detectable neuropsychological differences in early preclinical Alzheimer's disease: A meta-analysis. *Neuropsychology Review*, *27*(4), 305–325.

Hedden, T., Oh, H., Younger, A. P., & Patel, T. A. (2013). Meta-analysis of amyloid-cognition relations in cognitively normal older adults. *Neurology*, *80*(14), 1341–1348.

Jack, C. R., Bennett, D. A., Blennow, K., Carrillo, M. C., Dunn, B., Haeberlein, S. B., ... Karlawish, J. (2018). NIA-AA Research Framework: Toward a biological definition of Alzheimer's disease. *Alzheimer's & Dementia: The Journal of the Alzheimer's Association*, *14*(4), 535–562.

Jack, C. R., Bennett, D. A., Blennow, K., Carrillo, M. C., Feldman, H. H., Frisoni, G. B., ... Knopman, D. S. (2016). A/T/N: An unbiased descriptive classification scheme for Alzheimer disease biomarkers. *Neurology*, *87*(5), 539–547.

Jack, C. R., Dickson, D. W., Parisi, J. E., Xu, Y. C., Cha, R. H., O'Brien, P. C., ... & Kokmen, E. (2002). Antemortem MRI findings correlate with hippocampal neuropathology in typical aging and dementia. *Neurology*, *58*(5), 750-757.

Jack, C. R., Petersen, R. C., Xu, Y., O'Brien, P. C., Smith, G. E., Ivnik, R. J., ... & Kokmen, E. (2000). Rates of hippocampal atrophy correlate with change in clinical status in aging and AD. *Neurology*, *55*, 484–489.

Jack, C. R., Wiste, H. J., Weigand, S. D., Knopman, D. S., Mielke, M. M., Vemuri, P., ... Reyes, D. (2015). Different definitions of neurodegeneration produce similar amyloid/neurodegeneration biomarker group findings. *Brain*, *138*(12), 3747–3759.

Jack, C. R., Wiste, H. J., Weigand, S. D., Rocca, W. A., Knopman, D. S., Mielke, M. M., ... Petersen, R. C. (2014). Age-specific population frequencies of cerebral β -amyloidosis and neurodegeneration among people with normal cognitive function aged 50-89 years: A cross-sectional study. *Lancet Neurology*, *13*(10), 997-1005.

Jack, C. R., Wiste, H. J., Weigand, S. D., Therneau, T. M., Knopman, D. S., Lowe, V., ... Senjem, M. L. (2017). Age-specific and sex-specific prevalence of cerebral β -amyloidosis,

tauopathy, and neurodegeneration in cognitively unimpaired individuals aged 50–95 years: A cross-sectional study. *The Lancet Neurology*, 16(6), 435–444.

Johnson, S. C., Kosciak, R. L., Jonaitis, E. M., Clark, L. R., Mueller, K. D., Berman, S. E., ... Sager, M. A. (2018). The Wisconsin Registry for Alzheimer's Prevention: A review of findings and current directions. *Alzheimer's & Dementia: Diagnosis, Assessment & Disease Monitoring*, 10, 130–142.

Keihaninejad, S., Heckemann, R. A., Fagiolo, G., Symms, M. R., Hajnal, J. V., Hammers, A., & Alzheimer's Disease Neuroimaging Initiative. (2010). A robust method to estimate the intracranial volume across MRI field strengths (1.5T and 3T). *NeuroImage*, 50(4), 1427–1437.

Kinnunen, K. M., Cash, D. M., Poole, T., Frost, C., Benzinger, T. L., Ahsan, R. L., ... Malone, I. B. (2018). Presymptomatic atrophy in autosomal dominant Alzheimer's disease: A serial magnetic resonance imaging study. *Alzheimer's & Dementia*, 14(1), 43–53.

Klunk, W. E., Engler, H., Nordberg, A., Wang, Y., Blomqvist, G., Holt, D. P., ... Estrada, S. (2004). Imaging brain amyloid in Alzheimer's disease with Pittsburgh Compound-B. *Annals of Neurology: Official Journal of the American Neurological Association and the Child Neurology Society*, 55(3), 306–319.

Kuznetsova A, Brockhoff PB, Christensen RHB (2017). “lmerTest Package: Tests in linear mixed effects models.” *Journal of Statistical Software*, 82(13), 1–26.

Lehmann, M., Crutch, S. J., Ridgway, G. R., Ridha, B. H., Barnes, J., Warrington, E. K., ... & Fox, N. C. (2011). Cortical thickness and voxel-based morphometry in posterior cortical atrophy and typical Alzheimer's disease. *Neurobiology of Aging*, 32(8), 1466–1476.

McKhann, G. M., Knopman, D. S., Chertkow, H., Hyman, B. T., Jack, C. R., Kawas, C. H., ... Mayeux, R. (2011). The diagnosis of dementia due to Alzheimer's disease: Recommendations from the National Institute on Aging-Alzheimer's Association workgroups on diagnostic guidelines for Alzheimer's disease. *Alzheimer's & Dementia: The Journal of the Alzheimer's Association*, 7(3), 263–269.

Merluzzi, A. P., Vogt, N. M., Norton, D., Jonaitis, E., Clark, L. R., Carlsson, C. M., ... Zetterberg, H. (2019). Differential effects of neurodegeneration biomarkers on subclinical cognitive decline. *Alzheimer's & Dementia: Translational Research & Clinical Interventions*, 5, 129–138.

Mormino, E. C., Betensky, R. A., Hedden, T., Schultz, A. P., Amariglio, R. E., Rentz, D. M., ... Sperling, R. A. (2014). Synergistic effect of β -amyloid and neurodegeneration on cognitive decline in clinically normal individuals. *JAMA Neurology*, 71(11), 1379–1385.

Olsson, B., Lautner, R., Andreasson, U., Öhrfelt, A., Portelius, E., Bjerke, M., ... Strobel, G. (2016). CSF and blood biomarkers for the diagnosis of Alzheimer's disease: A systematic review and meta-analysis. *The Lancet Neurology*, 15(7), 673–684.

Patenaude, B., Smith, S. M., Kennedy, D. N., & Jenkinson, M. (2011). A Bayesian model of shape and appearance for subcortical brain segmentation. *NeuroImage*, *56*(3), 907–922.

Pettigrew, C., Soldan, A., Sloane, K., Cai, Q., Wang, J., Wang, M. C., ... & BIOCARD Research Team. (2017). Progressive medial temporal lobe atrophy during preclinical Alzheimer's disease. *NeuroImage: Clinical*, *16*, 439-446.

Price, J. L., McKeel, D. W., Buckles, V. D., Roe, C. M., Xiong, C., Grundman, M., ... Dickson, D. W. (2009). Neuropathology of nondemented aging: presumptive evidence for preclinical Alzheimer disease. *Neurobiology of Aging*, *30*(7), 1026–1036.

Price, J. L., & Morris, J. C. (1999). Tangles and plaques in nondemented aging and "preclinical" Alzheimer's disease. *Annals of Neurology*, *45*(3), 358–368.

R Core Team (2017). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing, Vienna, Austria. 2016.

Rey, A. (1941). L'examen psychologique dans les cas d'encéphalopathie traumatique. (Les problems.). *Archives de Psychologie*.

Roe, C. M., Fagan, A. M., Grant, E. A., Hassenstab, J., Moulder, K. L., Dreyfus, D. M., ... Holtzman, D. M. (2013). Amyloid imaging and CSF biomarkers in predicting cognitive impairment up to 7.5 years later. *Neurology*, *80*(19), 1784–1791.

Rosen, H. J., Gorno-Tempini, M. L., Goldman, W. P., Perry, R. J., Schuff, N., Weiner, M., ... Miller, B. L. (2002). Patterns of brain atrophy in frontotemporal dementia and semantic dementia. *Neurology*, *58*(2), 198–208.

Salat, D. H., Lee, S. Y., van der Kouwe, A. J., Greve, D. N., Fischl, B., & Rosas, H. D. (2009). Age-associated alterations in cortical gray and white matter signal intensity and gray to white matter contrast. *NeuroImage*. *48*(1), 21-28.

Schindler, S. E., Jasielc, M. S., Weng, H., Hassenstab, J. J., Grober, E., McCue, L. M., ... Fagan, A. M. (2017). Neuropsychological measures that detect early impairment and decline in preclinical Alzheimer disease. *Neurobiology of Aging*, *56*, 25–32.

Schott, J. M., Bartlett, J. W., Fox, N. C., & Barnes, J. (2010). Increased brain atrophy rates in cognitively normal older adults with low cerebrospinal fluid A β 1-42. *Annals of Neurology*, *68*(6), 825–834.

Schwarz, G. (1978). Estimating the dimension of a model. *The Annals of Statistics*, *6*(2), 461–464.

Soldan, A., Pettigrew, C., Fagan, A. M., Schindler, S. E., Moghekar, A., Fowler, C., ... Masters, C. L. (2019). ATN profiles among cognitively normal individuals and longitudinal cognitive outcomes. *Neurology*, *92*(14):e1567-e1579.

Soldan, A., Pettigrew, C., Cai, Q., Wang, M. C., Moghekar, A. R., O'Brien, R. J., ... & Albert, M. S.; BIOCARD Research Team. (2016). Hypothetical preclinical Alzheimer disease groups and longitudinal cognitive change. *JAMA Neurology*, 73(6), 698-705.

Stern, Y. (2017). An approach to studying the neural correlates of reserve. *Brain Imaging and Behavior*, 11(2), 410-416.

Storandt, M., Mintun, M. A., Head, D., & Morris, J. C. (2009). Cognitive decline and brain volume loss as signatures of cerebral amyloid- β peptide deposition identified with Pittsburgh compound B: cognitive decline associated with A β deposition. *Archives of Neurology*, 66(12), 1476-1481.

Strozyk, D., Blennow, K., White, L. R., & Launer, L. J. (2003). CSF A β 42 levels correlate with amyloid-neuropathology in a population-based autopsy study. *Neurology*, 60(4), 652-656.

Susanto, T. A. K., Pua, E. P. K., & Zhou, J. (2015). Cognition, brain atrophy, and cerebrospinal fluid biomarkers changes from preclinical to dementia stage of Alzheimer's disease and the influence of apolipoprotein e. *Journal of Alzheimer's Disease*, 45(1), 253-268.

Tapiola, T., Alafuzoff, I., Herukka, S.-K., Parkkinen, L., Hartikainen, P., Soininen, H., & Pirttilä, T. (2009). Cerebrospinal fluid β -amyloid 42 and tau proteins as biomarkers of Alzheimer-type pathologic changes in the brain. *Archives of Neurology*, 66(3), 382-389.

Tondelli, M., Wilcock, G. K., Nichelli, P., De Jager, C. A., Jenkinson, M., & Zamboni, G. (2012). Structural MRI changes detectable up to ten years before clinical Alzheimer's disease. *Neurobiology of Aging*, 33(4), 825. e25-825. e36.

van Maurik, I. S., Zwan, M. D., Tijms, B. M., Bouwman, F. H., Teunissen, C. E., Scheltens, P., ... van der Flier, W. M. (2017). Interpreting Biomarker Results in Individual Patients With Mild Cognitive Impairment in the Alzheimer's Biomarkers in Daily Practice (ABIDE) Project. *JAMA Neurology*, 74(12), 1481-1491.

van Rossum, I. A., Vos, S. J., Burns, L., Knol, D. L., Scheltens, P., Soininen, H., ... Minthon, L. (2012). Injury markers predict time to dementia in subjects with MCI and amyloid pathology. *Neurology*, 79(17), 1809-1816.

Vemuri, P., Wiste, H. J., Weigand, S. D., Shaw, L. M., Trojanowski, J. Q., Weiner, M. W., ... Initiative, A. D. N. (2009). MRI and CSF biomarkers in normal, MCI, and AD subjects predicting future clinical change. *Neurology*, 73(4), 294-301.

Villemagne, V. L., Burnham, S., Bourgeat, P., Brown, B., Ellis, K. A., Salvado, O., ... Maruff, P. (2013). Amyloid β deposition, neurodegeneration, and cognitive decline in sporadic Alzheimer's disease: a prospective cohort study. *The Lancet Neurology*, 12(4), 357-367.

Villemagne, V. L., Doré, V., Burnham, S. C., Masters, C. L., & Rowe, C. C. (2018). Imaging tau and amyloid- β proteinopathies in Alzheimer disease and other conditions. *Nature Reviews Neurology*, *14*(4), 225.

Vos, S. J., Gordon, B. A., Su, Y., Visser, P. J., Holtzman, D. M., Morris, J. C., ... Benzinger, T. L. (2016). NIA-AA staging of preclinical Alzheimer disease: discordance and concordance of CSF and imaging biomarkers. *Neurobiology of Aging*, *44*, 1–8.

Wang, L., Benzinger, T. L., Hassenstab, J., Blazey, T., Owen, C., Liu, J., ... & Ances, B. M. (2015). Spatially distinct atrophy is linked to β -amyloid and tau in preclinical Alzheimer disease. *Neurology*, *84*(12), 1254-1260.

Younes, L., Albert, M., Miller, M. I., & BIOCARD Research Team. (2014). Inferring changepoint times of medial temporal lobe morphometric change in preclinical Alzheimer's disease. *NeuroImage: Clinical*, *5*, 178-187.

8. Figure Captions

Figure 1: Immediate recall (sum of learning trials 1 through 5) from the Rey Auditory Verbal Learning Test. Lines depict model-predicted age trajectories for three values of $\text{ptau}_{181}/A\beta_{42}$: red represents -1 standard deviation from the mean; gray represents the mean value; blue represents +1 standard deviation from the mean. Each panel reflects the model fit at a particular value of global atrophy (columns; -1, 0, +1 SD from the mean) and hippocampal volume (rows; sim.). Model predictions were made assuming a male participant with 16.15 years of education (the mean level) and no prior exposure to the battery. Confidence bands reflect the standard error of prediction for each line. The overlaid scatter represents raw individual test score measurements within nine predictor value bins, grouped such that $Z_{\text{predictor}} \leq -0.5$ (top/left), $-0.5 < Z_{\text{predictor}} \leq 0.5$ (center/center), and $Z_{\text{predictor}} > 0.5$ (bottom/right).

Figure 2: Delayed recall from the Rey Auditory Verbal Learning Test. Lines depict model-predicted age trajectories for three values of $\text{ptau}_{181}/A\beta_{42}$: red represents -1 standard deviation from the mean; gray represents the mean value; blue represents +1 standard deviation from the mean. Each panel reflects the model fit at a particular value of global atrophy (columns; -1, 0, +1 SD from the mean) and hippocampal volume (rows; sim.). Model predictions were made assuming a male participant with 16.15 years of education (the mean level) and no prior exposure to the battery. Confidence bands reflect the standard error of prediction for each line. The overlaid scatter represents raw individual test score measurements within nine predictor value bins, grouped such that $Z_{\text{predictor}} \leq -0.5$ (top/left), $-0.5 < Z_{\text{predictor}} \leq 0.5$ (center/center), and $Z_{\text{predictor}} > 0.5$ (bottom/right).