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# Impact of sex and APOE- $\epsilon$ 4 genotype on patterns of regional brain atrophy in Alzheimer's Disease and healthy aging.

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## Abstract

Alzheimer's Disease (AD) is a heterogeneous disease that disproportionately affects women and people with the APOE- $\epsilon$ 4 susceptibility gene. We aim to describe the not-well-understood influence of both risk factors on the dynamics of brain atrophy in AD and healthy aging. Regional cortical thinning and brain atrophy were modeled over time using non-linear mixed-effect models and the FreeSurfer software. Covariance analysis was used to disentangle the effect of sex and APOE genotype on the regional onset age and pace of atrophy, while correcting for educational level. A map of the regions most affected by neurodegeneration is provided. Results were confirmed on gray matter density data from the SPM software. Women experience faster atrophic rates in the temporal, frontal, parietal lobes and limbic system and earlier onset in the amygdalas, but slightly later onset in the postcentral and cingulate gyri as well as all regions of the basal ganglia and thalamus. APOE- $\epsilon$ 4 genotypes leads to earlier and faster atrophy in the temporal, frontal, parietal lobes and limbic system in AD patients, but not in healthy patients. Higher education was found to slightly delay atrophy in healthy patients, but not for AD patients. A cohort of amyloid positive patients with MCI showed a similar impact of sex as in the healthy cohort, while APOE- $\epsilon$ 4 showed similar associations as in the AD cohort. Female sex is as strong a risk factor for AD as APOE- $\epsilon$ 4 genotype regarding neurodegeneration. Women experience a sharper atrophy in the later stages of the disease although not a significantly earlier onset. These findings may have important implications for the development of targeted intervention.

### Keywords:

Alzheimer's Disease, Longitudinal studies, Brain atrophy, Genetic covariates, Sexual dimorphism, Aging

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## 1. Introduction

Alzheimer's Disease (AD) is a neurodegenerative pathology that accounts for about 70% of the more than 55 millions dementia cases worldwide [1]. A silent phase, referred to as prodromal phase, shows accumulation of structural alterations in the brain without specific symptoms, eventually leading to a progressive cognitive decline that translates into a loss of the patient's autonomy for daily tasks, with impaired mnemonic, visuospatial and communicative functions as well as unusual behaviors such as paranoia and aggressiveness. For people under the age of 75, the incidence of AD has been estimated below 1.0%, while it reaches 8.4% [2, 3] for patients over 85, making older age the most important risk factor of the disease. Other risk factors have been identified with certainty and are briefly presented below.

The second most important risk factor is often said to be the presence of hereditary gene mutations [4]. More precisely, the inheritance of AD can be of two types. On one hand, rare autosomal dominant mutations in APP, PSEN1, and PSEN2, that encode amyloid precursors and presenilin proteins, leading to early-onset (<60 years old) familial AD, which accounts for roughly 5% of cases [4], and are often dismissed from studies on risk factors because of their low prevalence and understood causality. On the other hand, frequent gene polymorphisms, such as the  $\epsilon$ 4 and  $\epsilon$ 2 variants of the APOE gene, can influence susceptibility for roughly 50% of the common late-onset AD [4]. Genome wide association studies also identified a handful of other loci as potential risk factors, but thus far, the only gene variant considered to be an established risk factor for late onset AD is the APOE- $\epsilon$ 4 allele [5, 6, 1]. The APOE gene provides the blueprint for the apolipoprotein E that transports cholesterol in the bloodstream and helps bind A $\beta$  to cerebrospinal fluid, effectively clearing the brain of

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18 excess  $A\beta$ . The presence of  $\epsilon 4$  allele hinders  $A\beta$  clearance and leads to reduced neuronal injury response [7], and in turns  
19 correlate with higher AD risks.

20 The other genetic factor that is known to impact AD risk rates is the sex of patients. Two thirds of AD patients are  
21 women [1] and their cognitive decline is faster than for men [8]. By contrast, healthy aging tends to display delayed  
22 cognitive decline and structural alterations for women. [9] review conflicting studies on the topic of incidence rates and  
23 reach the conclusion that before the age of 75, no significant difference in incidence rates is detected, while incidence  
24 rates get significantly higher for women than for men after that inflexion point. The longer longevity of women has long  
25 been thought to be the sole cause for this discrepancy. However, the loss of the protective effects of estrogens during  
26 menopause, demonstrated in vitro and in vivo [10, 11], has also been suggested as a cause. Evidence also highlight a  
27 faster loss of autonomy but a longer lifespan after diagnosis for women [12]. These facts raise the question of a sexual  
28 dimorphism of AD. A precise understanding of the distinct patterns of structural and functional brain alterations over time  
29 is still lacking. Accurate descriptions of those patterns could help to implement better practices to care for both men and  
30 women. Besides, women are still underrepresented in clinical trials [13] and only 15% of trials report results stratified by  
31 sex [14], although this proportion increases in more recent studies. As suggested in [15], several gendered factors other  
32 than sex can also mediate the observed associations, although data is rarely available in large scales datasets.

33 Another often-mentioned risk factor is the education level. According to the cognitive reserve hypothesis, having more  
34 years of education increases the connections between neurons and enables the brain to compensate for the early changes of  
35 Alzheimer’s by using alternate routes of neuron-to-neuron communication to complete a cognitive task [16, 17]. Women  
36 are believed to benefit even more from higher education than men, albeit receiving less education [18]. [19] confirm that  
37 education is an indicator of cognitive reserve, but that the protective effects on cognition are depleted as neurodegenera-  
38 tion progresses.

39  
40 Building on the observation that the influence of sex on the progression of AD is not well understood, and that  
41 APOE- $\epsilon 4$  status is the strongest known genetic variant associated with AD, this work aims to describe the disentangled  
42 contributions of both those genetic factors on patterns of structural brain alterations, while accounting for biases due to  
43 varying education level. Such alterations, that are visible through MRI scans, reveal neurodegeneration occurring before  
44 the onset of the cognitive symptoms, and are thus crucial to understanding the early stages of the disease and for the design  
45 of drug trials. Leveraging the information from repeated measurements of cortical thicknesses and volumes of subcortical  
46 regions allows to describe each patient’s atrophic dynamics and compare across populations. Our goal is thus to provide  
47 a map of the brain regions that show significant correlation between sex or APOE- $\epsilon 4$  status and onset age and pace of  
48 regional atrophy. We provide this analysis for AD diagnosed and cognitively normal patients in order to emphasize the  
49 specificities of Alzheimer’s progression.

### 50 *1.1. Related work*

51 *Cross-sectional studies.* Over the course of AD progression, the link between cognitive decline and various covariates  
52 such as BMI [18], cardiac pathologies, APOE- $\epsilon 4$  genotype [20, 21, 22, 23] and sex have been explored, highlighting a  
53 higher impact of comorbidities and APOE- $\epsilon 4$  genotype for women on the severity of the disease symptoms. [24] and  
54 [25] review the state of knowledge about the differences across sexes in AD clinical manifestations, biomarkers patterns  
55 and risk factors.

56 On the other hand, healthy aging displays comparatively more spared alteration profiles for women compared to men,  
57 for both brain atrophy and cognitive decline. Seminal works dating back to the beginning of in-vivo imaging modalities  
58 report higher size decreases in men for average brain [26] and frontal and temporal lobes [27]. Many studies have since  
59 provided more insights into the differences between sexes for cognitive decline and link with comorbidities [28, 29],  
60 exhibiting opposite correlation than in Alzheimer’s studies. [30] exhibit associations between male sex, worse memory  
61 and higher hippocampal atrophy.

62 *Longitudinal studies.* The collection of repeated measurements of neuroimaging data and clinical assessment allows  
63 a finer understanding of pathological pathways. Notorious modeling approaches include event-based models [31, 32],

64 Gaussian-Process models [33, 34], Deep Learning methods [35, 36] and mixed-effects models. Application of such lon-  
65 gitudinal models are frequent for the assessment of cognitive decline [37, 38, 39, 40, 31, 41, 42, 43] but less used for  
66 imaging features. [44] advocate the use of linear mixed-effects models (LME) for progression models of neuroimaging  
67 data and apply LME to a mesh of control points of cortical thickness in a mass-univariate setting in [45]. [46] correlate  
68 these progression models with diagnosis in order to exhibit regions of the cortex that are most representative of the cog-  
69 nitive state of patients. Other studies also apply progression models to a few ROIs of the brain [47, 48, 49] in order to  
70 display the regions that correlate most with diagnosis. Applying this kind of modeling to a study of sex differences, [50]  
71 confirm that atrophy rates are higher for female than male patients and they decrease with age, while [51, 52] explain  
72 that brain volumes and cortical thicknesses are consistently smaller for cognitively normal males after accounting for age,  
73 and that the differences get smaller as cohorts are chosen at a more advanced state of cognitive decline, until they get  
74 indistinguishable for confirmed AD patients, with a sharper decline for women. Those study do not take into account  
75 important covariates such as APOE status and educational level, and do not disentangle the age of onset and the pace of  
76 atrophy. Many studies report the impact of APOE polymorphisms on brain atrophy for AD progression and link  $\epsilon 4$  with  
77 faster cortical thinning [53, 54] and hippocampal atrophy [55, 56], with increasing effects as patients get older [57].  
78

## 79 1.2. Contributions

80 Overall, many studies explored the differences between men and women regarding AD progression and healthy brain  
81 aging, as well as the influence of APOE polymorphisms. However, many of them rely on cross-sectional data that miss  
82 important information about the progression of the disease. Longitudinal tools have been proposed to leverage such in-  
83 formation, and have been successfully applied to biomarkers for disease progression models. However, these studies have  
84 either focused on the patterns of cognitive decline, or on a chosen set of ROIs to assess structural alterations, thus not  
85 providing a detailed map of the differences across the brain. Some longitudinal studies have proposed analysis of cortical  
86 thinning or brain atrophy with a high spatial resolution, however the focus has always been put on finding regions that  
87 correlate best with diagnosis in order to obtain valuable information about the brain alterations most specific to AD. To  
88 the best of our knowledge, no study has yet provided a quantitative comparison between male and female patterns of  
89 structural alterations over time, while accounting for APOE- $\epsilon 4$  genotype and education level, in order to provide a map of  
90 the brain regions that showcase distinct age-related alterations profiles. Besides, former works usually focus on the impact  
91 of one single factor, while only a joint analysis of both the genetic factors allows to isolate the contributions from each one.  
92

93 In this context, it seems relevant to further explore the differences between men and women regarding the onset  
94 and pace of alterations of the brain in both normal and AD progression, with a high degree of spatial resolution, while  
95 accounting for APOE- $\epsilon 4$  genotype and education level. Longitudinal studies allow to leverage information about the  
96 progression over time, while mixed-effect models allow for an interpretable modeling of each feature's trajectory across  
97 time. To sum up our contributions :

- 98 • We model regional cortical thinning and brain atrophy using non-linear mixed-effect models, and propose a formu-  
99 lation that disentangles the onset age and the pace of atrophy,
- 100 • for each region, we proceed to a multivariate regression for the individual parameters with regard to female sex,  
101 APOE- $\epsilon 4$  allele count and education level, in order to isolate the effect of each factor,
- 102 • we obtain a brain map of  $p$ -values that assess how significantly each factor influences the patterns of atrophy over  
103 time, when corrected for the other covariates,
- 104 • we display the regions that differ the most regarding onset age and pace of structural atrophy for the chosen covari-  
105 ate, for both healthy and AD progression.

106 This statistical pipeline addresses the lack of understanding of the influence of sex and APOE on structural brain  
107 alterations, and disentangles the joint effects of the multiple risk factors.



## 2. Material and Methods

*Data sets.* We performed the analysis on publicly available data from all waves (GO,1,2,3) of the Alzheimer’s Disease Neuroimaging Initiative (ADNI) database (adni.loni.usc.edu), as it provides repeated MRI scans for both cognitively normal elderlies and AD patients. The ADNI was launched in 2003 as a public-private partnership and its primary goal has been to test whether serial magnetic resonance imaging (MRI), positron emission tomography (PET), other biological markers, and clinical and neuropsychological assessment can be combined to measure the progression of mild cognitive impairment (MCI) and early Alzheimer’s disease (AD). All scans are quality-checked by trained anatomists. We selected all patients with at least 2 visits with a MRI scan and selected three cohorts : an AD cohort with patients with at least one confirmed AD diagnosis, an healthy cohort with patients who are diagnosed cognitively normal at every visit and an intermediate cohort of amyloid positive patients (see [58] for the chosen cutoffs) with at least one MCI diagnosis but no AD conversion. Patients with inconsistent AD diagnosis that revert to CN or MCI (107 patients) and amyloid negative patients (50 patients) are removed from the pathological cohort. Table 1 reports the demographics for the selected ADNI patients. The AD cohort is composed mostly of late-onset AD (566 patients) but also features a few early-onset cases (24 patients).

	AD cohort		A $\beta$ + MCI cohort		Healthy cohort	
	Male	Female	Male	Female	Male	Female
Patients ( $N$ )	329	261	262	176	210	264
Visits ( $N_{scan}$ )	1,447	1,092	1,164	794	1,063	1,169
Total follow-up (y)	3.7 $\pm$ 2.9	3.4 $\pm$ 3.0	4.5 $\pm$ 3.4	4.6 $\pm$ 3.3	4.6 $\pm$ 3.3	4.1 $\pm$ 3.0
Age at baseline	75.0 $\pm$ 7.1	73.6 $\pm$ 7.7	75.4 $\pm$ 7.5	71.5 $\pm$ 7.8	74.0 $\pm$ 6.1	72.7 $\pm$ 6.0
Education (y)	16.1 $\pm$ 2.8	14.7 $\pm$ 2.6	16.4 $\pm$ 2.8	15.5 $\pm$ 2.7	17.2 $\pm$ 2.4	16.1 $\pm$ 2.8
APOE- $\epsilon$ 4 (2/1/0)	69/163/97	44/133/84	32/99/121	24/71/81	5/51/154	7/75/182
MMSE	24.0 $\pm$ 4.0	23.2 $\pm$ 4.6	27.7 $\pm$ 2.0	28.2 $\pm$ 2.1	29.0 $\pm$ 1.2	29.2 $\pm$ 1.1
ADAS-Cog13	26.5 $\pm$ 10.6	29.2 $\pm$ 11.8	15.3 $\pm$ 6.9	12.6 $\pm$ 6.7	10.0 $\pm$ 4.6	8.3 $\pm$ 4.3

Table 1: Demographics for cohorts selected from ADNI. Numeric fields are in the form mean  $\pm$  standard deviation. (y) is years. (2/1/0) refers to the amount of APOE- $\epsilon$ 4 alleles. Cognitive scores are for all visits (not just baseline).

*Data processing.* These results have been obtained using the t1-freesurfer pipeline of Clinica [59]. This pipeline is a wrapper of different tools of the FreeSurfer (v6.0) software (<http://surfer.nmr.mgh.harvard.edu/>) [60]. This processing includes segmentation of subcortical structures (corpus callosum, ventral Diencephalon, choroid plexus, acum-bens area, amygdalas, hippocampi, caudate nuclei, putamen, pallidum and thalamus), extraction of cortical surfaces using the ”recon-all” pipeline, spatial normalization onto the FreeSurfer surface template (FsAverage) and cortical thickness estimation with respect to the 148 gyral and sulcal structures defined by the Destrieux atlas [61]. The subcortical volumes are normalized by intracranial volumes to account for the size of the head. Late releases of FreeSurfer have been demonstrated to yield similar atrophic rates to those obtained by manual segmentation for AD patients [62, 63].

In order to validate our findings on another modality, we extract gray matter density maps from the same t1-MRI data from ADNI. These features are obtained using the t1-volume pipeline of Clinica [59]. This pipeline is a wrapper of the Segmentation, Run Dartel (using a ADNI-based template) and Normalise to MNI Space routines implemented in the SPM12 software and yields a map of the average gray matter densities in each anatomical region defined in the AAL2 atlas [64], which splits the brain into 80 gyri and sulci for the cortex and 14 subcortical regions. It displays a similar granularity to the Destrieux atlas and allows comparison. Gray matter density is fundamentally different from cortical thicknesses and regional volumes, and could potentially exhibit different progression patterns, especially since it is well documented that women have on average more gray matter and less white matter than men after correcting for brain size, in most of the brain [65, 66, 67].

MRI images from ADNI are acquired with either 1.5T (3440 samples) or 3T (3289 samples) scanners. As noted in [68], Freesurfer outputs on 3T images are significantly thicker than for 1.5T images, which can hurt longitudinal

141 modeling and bias population-level comparisons. As is common in longitudinal studies, we proceed to bias correction  
 142 through histogram matching within each diagnosis group for each extracted feature.

143 *Longitudinal modeling.* Mixed-effects models describe each patient’s progression over time as a small variation – the  
 144 random effects of the model – around the average population trajectory – the fixed effects of the model. This study  
 145 focuses on univariate models, that are calibrated on the repeated measurements for one region of the cortex or subcortical  
 146 structure at a time. Linear mixed-effects models are widely used for longitudinal modeling and assume that features  
 147 evolve according to straight lines over time. Each patient is thus characterised by a slope and an intercept. The slope  
 148 can be interpreted as the pace of decline of a patient for the given feature, but the intercept is less meaningful. In that  
 149 setting, we choose to parametrize the inter-subjects variability as the combined effects of an individual onset age, and a  
 150 pace of decline as suggested in [41]. The onset age can be understood as a horizontal intercept and describes the age at  
 151 which a patient crosses the population-average-value threshold, and the pace of decline as the slope. Both these temporal  
 152 parameters allow to align all patients on a common progression timeline. Namely, given a family of feature observations  
 153  $\{y_{i,j}\}$  at times  $\{t_{i,j}\}$  for  $1 \leq i \leq N$  indexes the  $N$  patients and  $1 \leq j \leq N_i$  indexes the  $N_i$  visits of patient  $i$ , we resort to the  
 154 mixed-effect generative model

$$y_{i,j} = f\left(e^{\xi_i}(t_{i,j} - \tau_i) + t_0\right) + \varepsilon_{i,j}$$

155 where  $e^{\xi_i}$  and  $\tau_i$ , respectively the *progression pace* and *onset age* of patient  $i$  are called the individual parameters that  
 156 provide an affine time warp to account for the variability in pace and onset of decline between patients. These individual  
 157 parameters form the random effects of the model. We choose the Gaussian priors for the noise  $\varepsilon_{i,j} \sim \mathcal{N}(0, \sigma_\varepsilon^2)$  and random  
 158 effects  $\tau_i \sim \mathcal{N}(t_0, \sigma_\tau^2)$  and  $\xi_i \sim \mathcal{N}(0, \sigma_\xi^2)$ . In a linear mixed-effects framework,  $f$  is an affine function  $t \mapsto p_0 + v_0 * (t - t_0)$ ,  
 159 while for non-linear mixed-effects it is usually chosen to be the logistic function  $t \mapsto \left(1 + \left(\frac{1}{p_0}\right) \exp\left(\frac{-v_0 t}{p_0(1-p_0)}\right)\right)^{-1}$ . The  
 160 parameters  $p_0$ ,  $v_0$  and  $t_0$  are respectively a reference *position*, *velocity* and *time* and describe the average trajectory.  
 161 Together with the variances  $\sigma_\varepsilon, \sigma_\tau, \sigma_\xi$ , they form the fixed-effects of the model.

162 In practice, logistic regression is one of the most popular shape of trajectory, so all features should be normalized to  
 163 the range  $[0, 1]$ . We thus discard outliers using the so-called three sigma rule and add a min-max normalization within  
 164 each cohort, providing realistic asymptotes. Since cortical thicknesses and brain volumes decrease over time, we flip data  
 165 around  $.5$ , using the rotation  $x \mapsto 1 - x$ , in order to ensure increasingness, which is required for logistic modeling.

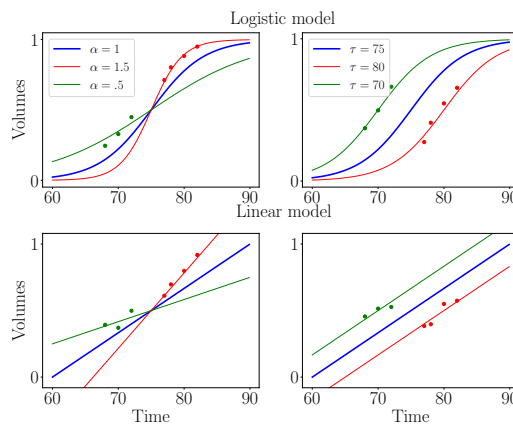


Figure 1: Illustration of logistic (first row) and linear (second row) mixed-effects models. Blue curve is the average trajectory (parametrized by  $t_0$ ,  $p_0$  and  $v_0$ ) and red and green curves illustrate the effect of progression pace ( $\alpha = e^{\xi}$ ) and onset age ( $\tau$ ), which allow to match individual measurements (isolated dots) to a continuous trajectory.

166 *Calibration of the model.* These longitudinal statistical models are part of a family of geometric models that have been  
 167 studied in [69] and [70]. We can proceed to a Maximum a Posteriori estimation of both random and fixed effects with  
 168 the MCMC-SAEM procedure in which the estimation step of an Expectation-Maximization algorithm is replaced by a  
 169 stochastic approximation. See [71] and [72] for details on this procedure, description of the complete likelihood and proof  
 170 of convergence and stability. One model is calibrated on each of the three cohorts. All analysis is done using the Leaspy  
 171 software.

172 *Logistic versus linear regression.* As mentioned above, the choice of  $f$  in the mixed-effect formulation should reflect the  
173 average progression of the feature. A few methods exist to learn the exact shape of the progression profile [73, 74] but  
174 add a strong computational burden. We compared the two most widespread available shapes, namely linear and logistic  
175 curves, in order to assess the stability of convergence as well as the estimated noise of the longitudinal fit. The logistic  
176 curve marginally surpassed the linear curve for both these criteria.

177 *Goodness of fit.* In order to ensure that the longitudinal models accurately describe the atrophy of each feature, we  
178 compare the distributions of reconstruction errors (the differences between the predicted values of the models at the time  
179 of each visit and the actual measurements) for the three cohorts to the distribution of measurements noise. Imaging data are  
180 indeed subject to variations in the experimental conditions and in the processing pipeline. In order to evaluate this noise,  
181 some visits are acquired twice within a few hours. For ADNI, we dispose of 1604 duplicate images from 285 different  
182 patients. We provide boxplots that display the empirical distributions of test/re-test errors and of the reconstruction errors  
183 for the three cohorts in supplementary materials. Distributions largely overlap, and reconstruction errors fall close to the  
184 measurements uncertainty, which hints that our models could not be improved without overfitting. Additionally, it is  
185 important to note that the reconstruction errors are not biased regarding sex, APOE status, education level, ADNI phases  
186 nor field strength.

187 *Statistical analysis.* Once the univariate models are calibrated, we have a family of patient-wise onset ages and progres-  
188 sion paces for each feature. We can thus proceed to statistical testing of the differences between subgroups. To do so,  
189 we perform covariance analysis using ordinary least squares to regress the individual parameters with regard to female  
190 sex, number of APOE- $\epsilon$ 4 alleles and education level of each patient. This evaluates the impact of each covariate after  
191 correcting for the other ones, and also the significance of the corresponding association. Since we are in a multiple testing  
192 setting, we use False Discovery Rate (FDR) [75] to obtain a map of corrected  $p$ -values that assess how certain it is that  
193 the chosen covariate influences the onset or pace of atrophy for each region. Given the high number of statistical tests  
194 (one for each of the 148 regions of the Destrieux atlas), a more stringent correction method such as Family-Wise Error  
195 Rates would be unsuitable as it would discard significant correlations. Absolute pairwise-correlations between covariates  
196 are .02 for APOE/sex, .05 for APOE/education and .18 for sex/education, which means that regressing with regards to the  
197 education level might mitigate the strength of the observed sexual dimorphism, but interactions between covariates are  
198 less likely for the other pairs.

199 *Interpretability of the  $p$ -values.* For each feature, patients are aligned on a common timeline with the individual onset  
200 age and pace of atrophy. One can, for instance, observe that for the inferior temporal gyrus, cortical thinning occurs on  
201 average 1.5 years earlier for each copy of the  $\epsilon$ 4 allele, and on average 23% faster for women, after correcting for the  
202 other covariates. However these multiple timelines are learned independently and cannot be compared directly in order to  
203 exhibit the regions that are mostly affected by a covariate, as it may not be statistically significant. Resorting to statistical  
204 testing, using t-tests under the null hypothesis that the regression coefficient is 0, allows to circumvent this issue as it  
205 normalizes all the effect sizes by the natural temporal scale associated with the region. Besides, for a fixed sample size,  
206  $p$ -values are monotonically related to effect sizes, so lower corrected  $p$ -values can be interpreted as indicative of a bigger  
207 impact of the covariate, and allow comparison across brain regions and covariates.

208

209 We provide a map of cortical regions and a list of sub-cortical volumes that display significant differences when  
210 stratified for sex or APOE- $\epsilon$ 4 status, regarding onset age and pace of atrophy, for AD, amyloid positive MCI and healthy  
211 aging. Corrected  $p$ -values higher than .05 are discarded and the remaining  $p$ -values are presented in logarithmic scale  
212 (base 10) for cortical thinning maps.

### 213 3. Results

214 Scales of log  $p$ -values vary between each plot and should be taken into account to evaluate the strength of the consid-  
215 ered risk factor. For visualization purposes, cortical thinning maps are presented by cohort (AD in Fig. 2, control cohort  
216 in Fig. 3 and MCI in Fig. 4) while all results for subcortical volumes are compiled in Table. 2.

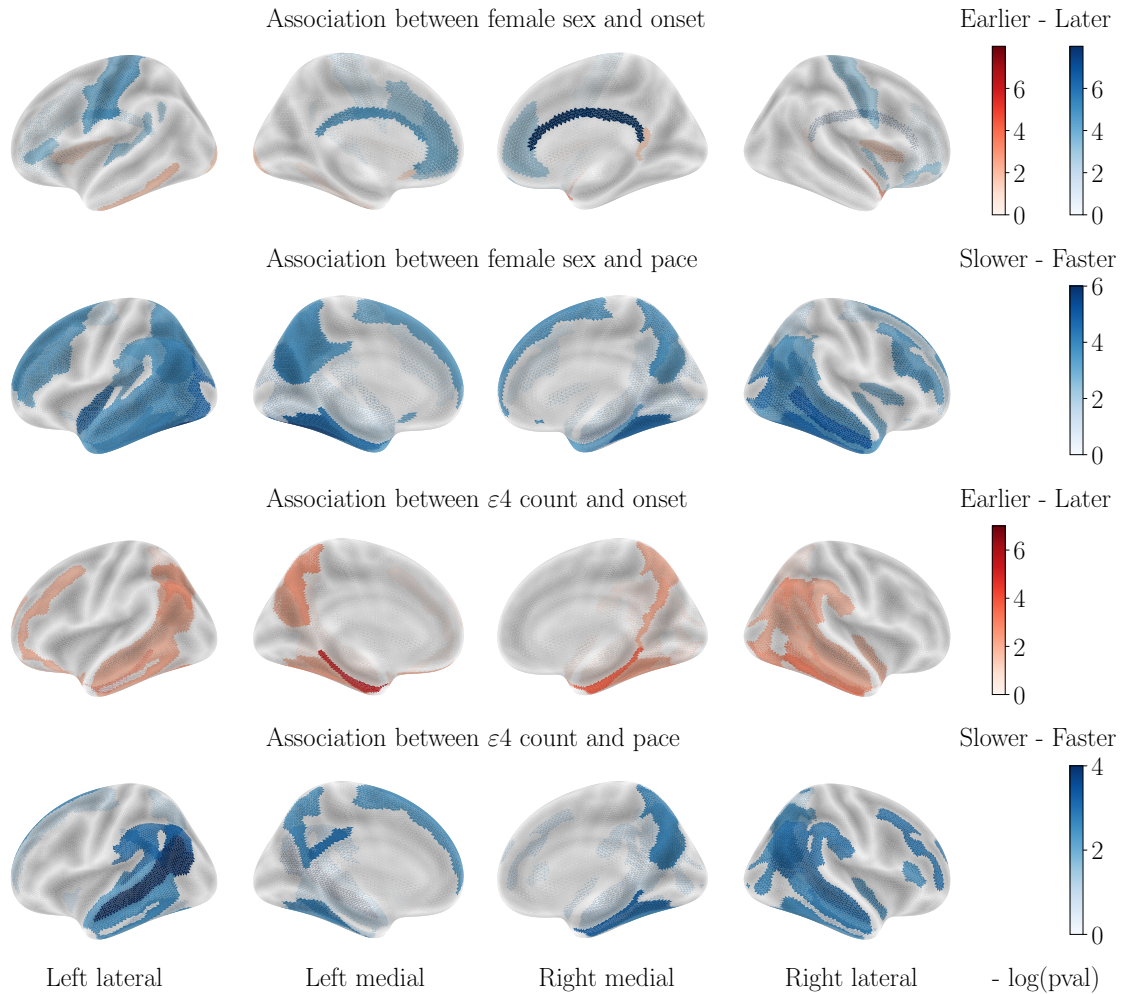


Figure 2: Cortical thinning over the course of AD progression. Legend bars shows negative  $\log p$ -values. It should be noted that blue values indicate that the considered covariate (female sex or APOE- $\epsilon 4$  genotype) is a protective factor for onset age but a risk factor for pace of atrophy, since higher onset age is better but higher progression pace is worse.

217 *Impact of sex on cortical thinning for AD progression.* Almost all regions of the cortex display a significantly higher  
 218 progression pace for female patients, with the exception of the motor cortex, sensory areas and inferior frontal lobe.  
 219 Regions that are most accelerated in females are the entire temporal lobe, the middle and superior frontal lobe, the entire  
 220 occipital lobe and the anterior and medial parietal lobe. Onset ages are, on the other hand, more homogeneous across  
 221 sexes. The motor cortex, the cingulate gyrus and the medial parietal lobe display an earlier onset for men, while the  
 222 inferior temporal lobe and inferior frontal lobe display an earlier onset age for female patients. All other regions do not  
 223 allow to reject the null hypothesis.

224 *Impact of APOE- $\epsilon 4$  genotype on cortical thinning for AD progression.* Almost all regions of the cortex also display a  
 225 significantly higher progression pace for APOE- $\epsilon 4$  carriers. The most affected regions are located roughly in the same  
 226 areas as for the impact of sex, but with different regions of highest intensity, and an overall lower effect. The temporal  
 227 lobe, the parietal lobe and the frontal lobe also display an earlier onset for APOE- $\epsilon 4$  carriers. The region that presents the  
 228 most advanced onset for  $\epsilon 4$  carriers is the hippocampal gyrus.

229 *Impact of sex on cortical thinning for healthy aging.* Contrary to what was seen in AD progression, the sexual dimorphism  
 230 for healthy aging manifests mainly through a significantly earlier onset age for male subjects, especially in the parietal  
 231 and frontal lobes. Only the inferior temporal lobe and subcallosal gyrus display a slightly earlier onset for women. On the  
 232 other hand, progression paces are similar across sexes except for the cingulate gyrus that is much accelerated in female  
 233 patients, while a few regions of the parietal lobe display a higher pace of atrophy for male patients.

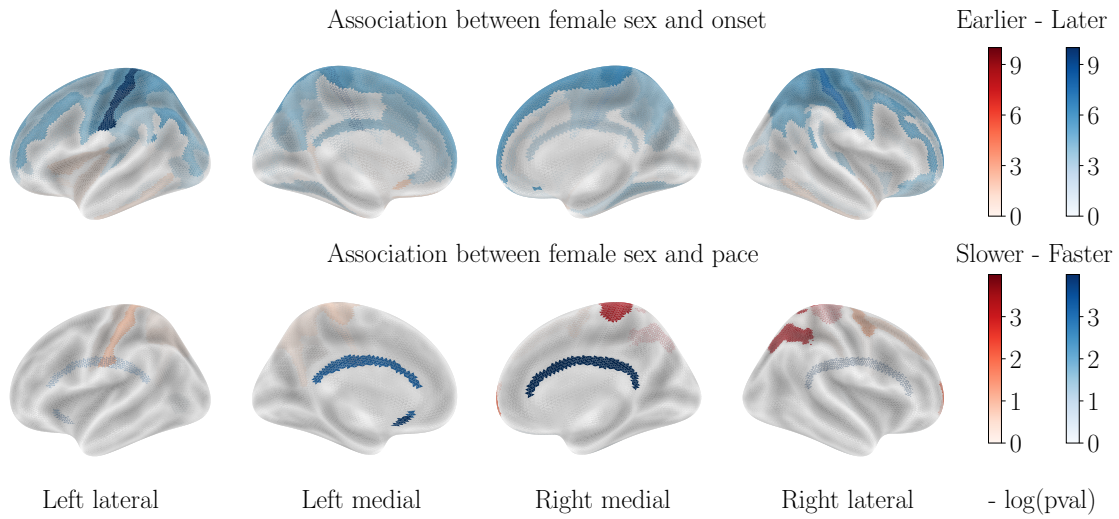


Figure 3: Cortical thinning over the course of cognitively normal aging. Associations with APOE- $\epsilon 4$  status are not displayed as they are not significant.

234 *Impact of APOE- $\epsilon 4$  genotype on cortical thinning for healthy aging.* In order to assess the impact of the APOE- $\epsilon 4$   
 235 genotype on cognitively normal aging, we also stratified regarding this factor. Interestingly, the  $\epsilon 4$  allele carriers do not  
 236 display significantly different patterns for cortical thinning across healthy aging, which leads to believe that APOE- $\epsilon 4$  by  
 237 itself does not cause the accelerated atrophy of the brain but only serves as one cog of the unraveling of AD. It should be  
 238 noted however that the small amount of  $\epsilon 4$  carriers in the healthy cohort can bias this result.

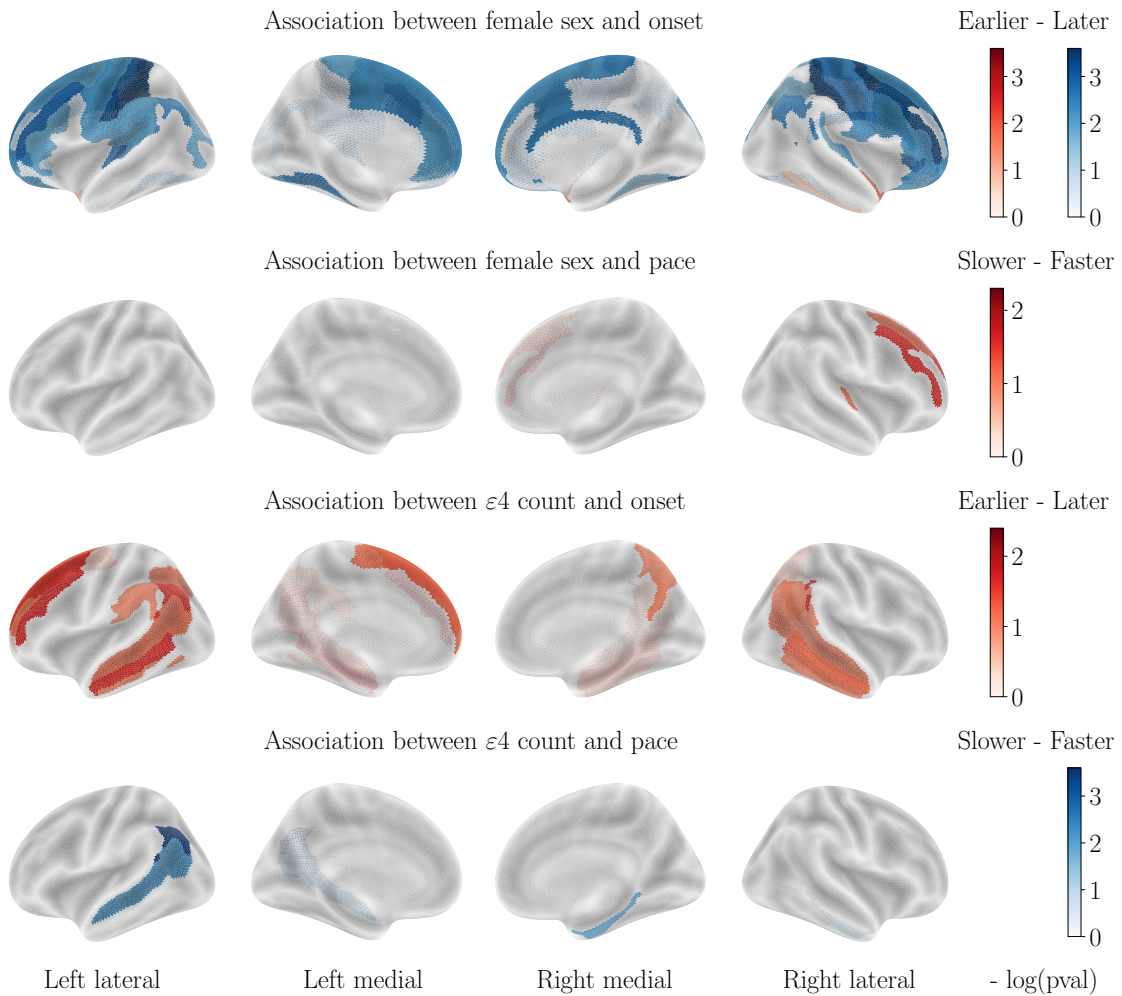


Figure 4: Cortical thinning over the course of MCI patients' aging.

239 *Influence of both covariates for patients with MCI.* The progression paces show little significant correlation with both  
 240 covariates, however, for onset age the correlations with sex are similar to those displayed for healthy aging while the  
 241 correlations with APOE- $\epsilon$ 4 status are similar to those displayed for AD progression, although of a weaker effect.

242 *Correlations with the patterns of atrophy for subcortical structures.* For healthy aging, male sex correlates with an earlier  
 243 onset age for most regions with no significant differences in pace of atrophy, while no significant correlation is found for  
 244 APOE- $\epsilon$ 4 genotype. For the AD cohort on the other hand, female sex correlates with an earlier onset for most regions, and  
 245 higher paces of the hippocampi and bilateral amygdalas while APOE- $\epsilon$ 4 genotype correlates with earlier onset and higher  
 246 pace for the hippocampi and bilateral amygdalas. We reach the same conclusion regarding the MCI cohort as for cortical  
 247 thinning : sex correlates with atrophy in a similar fashion to the healthy cohort, while APOE- $\epsilon$ 4 genotype correlates in a  
 248 similar fashion to the AD cohort. Regions without significant correlations are not displayed.

		Correlations with sex			Correlations with APOE- $\epsilon$ 4		
		$p_{val}$ CN	$p_{val}$ MCI	$p_{val}$ AD	$p_{val}$ CN	$p_{val}$ MCI	$p_{val}$ AD
Amygdala (L)	Onset	-	-	8.1e-03	-	4.9e-03	1.9e-07
	Pace	-	-	1.2e-06	-	2.2e-03	7.0e-06
Amygdala (R)	Onset	-	-	7.4e-05	-	3.2e-02	1.4e-06
	Pace	-	-	2.3e-05	-	2.5e-05	1.9e-02
Caudate (L)	Onset	5.5e-07	6.7e-04	1.7e-04	-	-	-
	Pace	-	-	-	-	-	-
Caudate (R)	Onset	1.2e-04	1.8e-04	8.3e-04	-	-	-
	Pace	-	-	-	-	-	-
Hippocampus (L)	Onset	4.7e-06	1.2e-02	-	-	3.0e-03	1.5e-07
	Pace	-	-	3.9e-05	-	5.7e-04	1.2e-02
Hippocampus (R)	Onset	1.1e-04	1.2e-02	-	-	2.1e-03	1.1e-09
	Pace	-	-	1.2e-04	-	3.9e-04	2.6e-02
Pallidum (L)	Onset	4.6e-04	6.9e-04	4.9e-02	-	-	-
	Pace	-	-	-	-	-	-
Pallidum (R)	Onset	6.5e-03	1.8e-04	3.1e-05	-	-	-
	Pace	-	-	-	-	-	-
Thalamus (L)	Onset	1.3e-06	7.8e-12	1.5e-07	-	-	-
	Pace	-	1.1e-02	-	-	-	-
Thalamus (R)	Onset	4.1e-06	4.6e-09	5.5e-08	-	-	-
	Pace	-	-	-	-	-	-

Table 2: Significant correlations with subcortical atrophy. For all the significant features, APOE- $\epsilon$ 4 genotype correlate with lower onset age and higher pace, and female sex correlates with higher onset age and higher pace, although correlations with pace are rare and only present in AD and MCI cohorts.

249 *Differences between left and right hemisphere.* For AD progression, the left hemisphere displays more regions that dif-  
 250 fer significantly for both sex and APOE- $\epsilon$ 4 stratification, but the associated t-values do not significantly differ between  
 251 hemispheres. This confirms that atrophic patterns are asymmetric but not completely lateralized [76].

252 *Impact of education level.* Fig. 5 illustrates the impact of education level on cortical thinning patterns, after accounting  
 253 for sex and APOE- $\epsilon$ 4 status. Correlations are only found in the healthy cohort, and higher education level correlates  
 254 with higher onset age for the postcentral gyrus, the medial parietal and medial occipital lobes, as well as the left superior  
 255 temporal lobe, and lower pace of atrophy for parts of the frontal and occipital lobes. No significant correlation is found  
 256 for the AD cohort, in line with former studies [77]. For subcortical volumes, only the hippocampal atrophy is delayed for  
 257 more educated healthy patients, and no significant correlation is found for AD patients. One hypothesis is that education  
 258 level is not, in itself, helping delay the atrophy for healthy controls, but acts as a proxy of lifestyle healthiness, which  
 259 influences metabolic pathways and brain atrophy. In AD cohort, that small preserving effect is likely to be cancelled by  
 260 the influence of other covariates that cause massive atrophy.



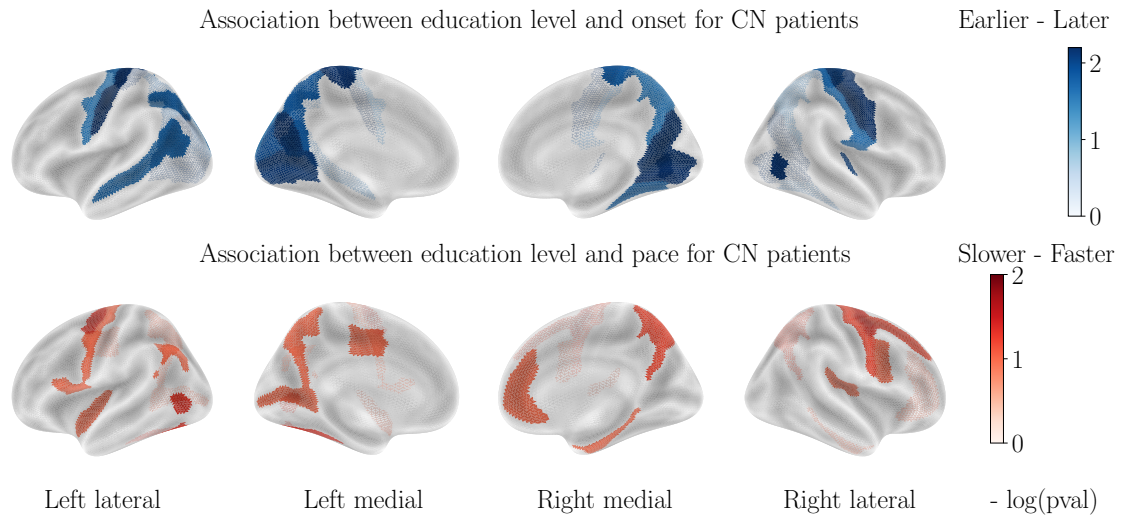


Figure 5: Correlation between education level and cortical thinning dynamics for CN patients. Correlations observed for the AD patients are not significant and thus not displayed.

261 *Validation on gray matter density maps from ADNI.* Despite the strong sexual dimorphism in regional gray/white matter  
 262 ratios, we recover most results from the main analysis. For AD patients, the same regions display a strong dimorphism :  
 263 almost all of the temporal lobe, frontal lobe and occipital lobe display a much stronger atrophic pace for women, while the  
 264 postcentral gyrus displays an earlier onset for men. APOE- $\epsilon 4$  allele also correlates with a faster pace and earlier onset in  
 265 the medial temporal and parietal lobes, as well as in the temporal lobe and parts of the frontal lobe. For CN patients, we  
 266 recover the absence of association with APOE genotype, while men display a much earlier onset for almost all regions  
 267 (with emphasis on the parietal lobe and postcentral gyrus), while a few isolated regions of the frontal and temporal lobe  
 268 display an faster pace of decline for men. The conclusions regarding the MCI cohort and the impact of education level  
 269 are also confirmed. The differences with the main analysis are thus only a matter of a few isolated regions and of the  
 270 order of magnitude of the statistical associations. We provide the association figures for cortical thinning and the tables  
 271 for subcortical structures in supplementary materials.

272 *Major takeaways.* Our study allows to isolate the contributions from sex, APOE status and education level on both onset  
 273 age and pace of atrophy for each region of the cortex and brain, while accounting for the other covariates. We find that :

- 274 • Sex is as important a risk factor as APOE- $\epsilon 4$  genotype for cortical thinning and brain atrophy for AD patients, as  
 275 both stratifications yield effect sizes that are not significantly different.
- 276 • Female AD patients decline much faster than male patients, however, the onset of the atrophy is still earlier for male  
 277 patients, in line with the healthy aging patterns. This suggests that the disease strikes female patients with much  
 278 more intensity, but do not present an earlier onset. This point is revealed by the use of longitudinal studies and has  
 279 important implications for practitioners for the follow-up of patients.
- 280 • Education level seems to be a protective factor for healthy patients but is not significant in AD progression.
- 281 • For the MCI cohort, the influence of sex is similar to that of the healthy cohort, while the effect of APOE- $\epsilon 4$   
 282 genotype is similar to that of the AD cohort, although of an overall weaker effect.

#### 283 4. Discussion

284 Several limitations and design choices need to be acknowledged in order to put results in perspective.

285 *Clinical characterization of diagnosis in ADNI.* For the control cohort, we used the CN patients in ADNI, because it  
 286 allows a fair comparison between AD progression and cognitively normal aging, without acquisition biases. Since ADNI  
 287 is not an epidemiological study on healthy aging, the cognitively normal patients may not represent accurately the general

288 population because of ADNI's inclusion criteria. For the MCI cohort, it is important to note that MCI is a cognitive status  
289 defined by subjective memory complaints and does not always lead to AD as other factors can cause patients to have it.  
290 The prevalence of MCI symptoms are found to be between 15 and 20% for patients over 60 years old [78], and roughly 8  
291 to 15% of these convert to AD each year [79]. In order to make the cohort less heterogeneous, we decided to only keep  
292 amyloid positive patients in order to interpret this cohort as describing AD pathogenesis. [80] assert that the recruited  
293 cohorts for CN, MCI and AD patients successfully describe the associated clinical status.

294 *Validation cohort.* Reproducing this study is complicated because of the lack of publicly available longitudinal database  
295 of the same scale as ADNI, and the difficulty to fit longitudinal models to pooled databases with varying protocols. Our  
296 statistical pipeline requires to split the patients between CN and AD patients, while only keeping patients with more than  
297 2 visits with a t1-MRI scan. For instance with those criteria, in the Australian Imaging Biomarkers and Lifestyle Study of  
298 Aging (AIBL), often used to validate findings on ADNI, the AD cohort only contains 38 patients with a total 105 visits,  
299 and the healthy cohort 128 patients with 431 visits, before the additional stratification by sex or APOE- $\epsilon$ 4 genotype.  
300 The sample sizes are thus too small to provide enough statistical power to reproduce the regional map of significant  
301 correlations.

302 *Impact of the chosen atlas.* It must be taken into account that the choice of different atlas might yield different results. One  
303 anatomical region that is positively associated with a covariate can span many ROIs or on the other hand be split between  
304 ROIs and prevent the detection of the true underlying association. On the other hand, our mixed-effect formulation cannot  
305 be fitted directly to vertex-wise thickness measurements because the onset age (or horizontal intercept) will not converge  
306 for features that display little progression compared to the feature noise.

307 *Regions normalization.* Since subcortical regions' volumes are correlated with the volumes of the skull and brain, it is  
308 standard practice to normalize by the intracranial volume in order to allow a fair comparison between subjects. The impact  
309 of such normalization is discussed in former studies : in [81, 82, 83] authors suggest that subcortical volumes should be  
310 normalized with total intracranial volume, while cortical thicknesses should not, for diagnosis prediction and progression  
311 models. On the other hand, [84] find that cortical thicknesses should be normalized with either intracranial volume or  
312 average thickness to help predict the cognitive status of a patient. [65] discuss the effect of normalizing cortical thicknesses  
313 to allow a fair comparison between healthy male and female subjects. Allometric scaling is often used to circumvent this  
314 issue, but [85] find that allometric and linear scaling yield similar effect sizes and coefficients when evaluating the effect  
315 of sex and age on brain measurements.

316 *Interpretability of the onset age.* As opposed to the straightforward pace of atrophy, the onset age needs to be interpreted  
317 with caution. It represents the age at which a patient crosses a chosen threshold (chosen to be the average value for  
318 the whole cohort). Brain atrophy does not have a well-defined starting point and the notion of onset age is thus to be  
319 understood with regard to a reference point in the average progression. For instance, the earlier onset ages for men in the  
320 CN cohort can be understood as describing the fact that cortical thicknesses are significantly thinner than for women. Since  
321 the difference in onset gets way smaller for the AD cohort, it agrees with former findings that the gap between men and  
322 women closes as neurodegeneration progresses, with a greater pace of decline for women in the late stages of the disease  
323 [51, 52].

324 *Clinical implications.* The discrepancies in alteration patterns of the brain between sexes and APOE genotypes reinforce  
325 the idea that the disease manifests differently between subpopulation and care should be provided accordingly. Besides,  
326 clinical trials that monitor the effect of a drug on neurodegeneration should put an emphasis on both having more repre-  
327 sentative demographics after enrolment, and evaluating the impact of drugs in a stratified manner as patients are likely to  
328 react differently to the drug depending on both the explored genetic risk factors. It is also interesting to note that most re-  
329 gions significantly affected by the considered risk factors are known to be associated with AD (e.g. medial temporal lobe,  
330 limbic system, frontal lobe, etc). This work could be interpreted jointly with studies that describe the sexual differences in  
331 associations between cortical thickness and cognition such as [52] in order to provide a complete description of the sexual  
332 dimorphism of neurodegeneration and its link with AD cognitive symptoms.



333 *Perspectives.* This statistical pipeline can be applied to other modalities of neuroimaging data. For instance, [86] applies  
334 the same statistical pipeline to FDG-PET scans instead of structural MRI in order to assess the sexual dimorphism of AD  
335 and influence of APOE genotype regarding brain hypometabolism, which complements the study of brain atrophy. Other  
336 imaging modalities specific to AD, such as amyloid-PET or tau-PET, are also under investigation within this pipeline. A  
337 strong sexual dimorphism for the spreading patterns of pathological protein tangles in the brain would prompt the latest  
338 clinical trials, that choose amyloid load as a primary disease outcome, to put great care in evaluating the differentiated  
339 results between male and female patients.

## 340 **5. Conclusion**

341 Structural alterations of the brain happen before the onset of cognitive decline and the collection of MRI-derived  
342 features reveals varying patterns of atrophy between subgroups of patients. Female sex, APOE- $\epsilon$ 4 genotype and low  
343 education level have been identified as the biggest risk factors for cognitive decline, but their impact on early-stage  
344 structural alterations is not yet well understood. In this work we described the disentangled effects of these 3 covariates  
345 on the onset and pace of regional atrophy and cortical thinning. This reveals that female sex is actually as strong a risk  
346 factor for neurodegeneration as APOE- $\epsilon$ 4 genotype, and women experience much faster atrophic rates after correcting for  
347 the APOE genotype. APOE- $\epsilon$ 4 genotype leads to earlier and faster atrophy for most regions of the brain for AD patients  
348 but not for healthy patients. Healthy patients with higher education experience slightly delayed atrophy but not patients  
349 with neurodegeneration. The results were validated with congruent findings from the same study applied to the regional  
350 loss of gray matter density. This work calls for further exploration of the sexual dimorphism of AD regarding structural  
351 alterations.

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358  
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360 in studies involving human participants were in accordance with the ethical standards of the institutional and/or national  
361 research committee and with the 1964 Helsinki declaration and its later amendments. More details can be found at  
362 [adni.loni.usc.edu](http://adni.loni.usc.edu). (This article does not contain any studies with human participants performed by any of the authors).

363

## References

- [1] Alzheimer's Association *et al.*, "2016 alzheimer's disease facts and figures," *Alzheimer's & Dementia* **12**(4), 459–509 (2016).
- [2] L. E. Hebert, P. A. Scherr, L. A. Beckett, *et al.*, "Age-specific incidence of alzheimer's disease in a community population," *Jama* **273**(17), 1354–1359 (1995).
- [3] L. Hebert, J. Bienias, N. Aggarwal, *et al.*, "Change in risk of alzheimer disease over time," *Neurology* **75**(9), 786–791 (2010).
- [4] R. E. Tanzi, "The genetics of alzheimer disease," *Cold Spring Harbor perspectives in medicine* **2**(10), a006296 (2012).
- [5] A. M. Saunders, W. J. Strittmatter, D. Schmechel, *et al.*, "Association of apolipoprotein e allele 4 with late-onset familial and sporadic alzheimer's disease," *Neurology* **43**(8), 1467–1467 (1993).
- [6] L. A. Farrer, L. A. Cupples, J. L. Haines, *et al.*, "Effects of age, sex, and ethnicity on the association between apolipoprotein e genotype and alzheimer disease: a meta-analysis," *Jama* **278**(16), 1349–1356 (1997).
- [7] R. W. Mahley and Y. Huang, "Apolipoprotein e sets the stage: response to injury triggers neuropathology," *Neuron* **76**(5), 871–885 (2012).
- [8] K. R. Laws, K. Irvine, and T. M. Gale, "Sex differences in cognitive impairment in alzheimer's disease," *World journal of psychiatry* **6**(1), 54 (2016).
- [9] C. R. Beam, C. Kaneshiro, J. Y. Jang, *et al.*, "Differences between women and men in incidence rates of dementia and alzheimer's disease," *Journal of Alzheimer's Disease* **64**(4), 1077–1083 (2018).
- [10] A. Członkowska, A. Ciesielska, G. Gromadzka, *et al.*, "Gender differences in neurological disease," *Endocrine* **29**(2), 243–256 (2006).
- [11] A. R. Genazzani, N. Pluchino, S. Luisi, *et al.*, "Estrogen, cognition and female ageing," *Human reproduction update* **13**(2), 175–187 (2007).
- [12] E. Sinforiani, A. Citterio, C. Zucchella, *et al.*, "Impact of gender differences on the outcome of alzheimer's disease," *Dementia and geriatric cognitive disorders* **30**(2), 147–154 (2010).
- [13] J. Martinkova, F.-C. Quevenco, H. Karcher, *et al.*, "Proportion of women and reporting of outcomes by sex in clinical trials for alzheimer disease: a systematic review and meta-analysis," *JAMA Network Open* **4**(9), e2124124–e2124124 (2021).
- [14] J. B. Schwartz and S. Weintraub, "Treatment for alzheimer disease—sex and gender effects need to be explicitly analyzed and reported in clinical trials," *JAMA network open* **4**(9), e2124386–e2124386 (2021).
- [15] M. M. Mielke, "Sex and gender differences in alzheimer's disease dementia," *The Psychiatric times* **35**(11), 14 (2018).
- [16] C. M. Roe, C. Xiong, J. P. Miller, *et al.*, "Education and alzheimer disease without dementia: support for the cognitive reserve hypothesis," *Neurology* **68**(3), 223–228 (2007).
- [17] Y. Stern, "Cognitive reserve in ageing and alzheimer's disease," *The Lancet Neurology* **11**(11), 1006–1012 (2012).
- [18] S. Subramaniapillai, S. Rajagopal, J. Snytte, *et al.*, "Sex differences in brain aging among adults with family history of alzheimer's disease and apoe4 genetic risk," *NeuroImage: Clinical* **30**, 102620 (2021).
- [19] D. Mungas, B. Gavett, E. Fletcher, *et al.*, "Education amplifies brain atrophy effect on cognitive decline: implications for cognitive reserve," *Neurobiology of Aging* **68**, 142–150 (2018).
- [20] A. Altmann, L. Tian, V. W. Henderson, *et al.*, "Sex modifies the apoe-related risk of developing alzheimer disease," *Annals of neurology* **75**(4), 563–573 (2014).
- [21] F. Sampedro, E. Vilaplana, M. J. De Leon, *et al.*, "Apoe-by-sex interactions on brain structure and metabolism in healthy elderly controls," *Oncotarget* **6**(29), 26663 (2015).
- [22] S. C. Neu, J. Pa, W. Kukull, *et al.*, "Apolipoprotein e genotype and sex risk factors for alzheimer disease: a meta-analysis," *JAMA neurology* **74**(10), 1178–1189 (2017).

- [23] R. F. Buckley, E. C. Mormino, R. E. Amariglio, *et al.*, “Sex, amyloid, and apoe  $\epsilon$ 4 and risk of cognitive decline in preclinical alzheimer’s disease: Findings from three well-characterized cohorts,” *Alzheimer’s & Dementia* **14**(9), 1193–1203 (2018).
- [24] M. T. Ferretti, M. F. Iulita, E. Cavedo, *et al.*, “Sex differences in alzheimer disease—the gateway to precision medicine,” *Nature Reviews Neurology* **14**(8), 457–469 (2018).
- [25] K. R. Laws, K. Irvine, and T. M. Gale, “Sex differences in alzheimer’s disease,” *Current opinion in psychiatry* **31**(2), 133–139 (2018).
- [26] C. E. Coffey, J. F. Lucke, J. A. Saxton, *et al.*, “Sex differences in brain aging: a quantitative magnetic resonance imaging study,” *Archives of neurology* **55**(2), 169–179 (1998).
- [27] P. E. Cowell, B. I. Turetsky, R. C. Gur, *et al.*, “Sex differences in aging of the human frontal and temporal lobes,” *Journal of Neuroscience* **14**(8), 4748–4755 (1994).
- [28] A. C. McCarrey, Y. An, M. H. Kitner-Triolo, *et al.*, “Sex differences in cognitive trajectories in clinically normal older adults.,” *Psychology and aging* **31**(2), 166 (2016).
- [29] N. M. Armstrong, Y. An, L. Beason-Held, *et al.*, “Sex differences in brain aging and predictors of neurodegeneration in cognitively healthy older adults,” *Neurobiology of aging* **81**, 146–156 (2019).
- [30] C. R. Jack, H. J. Wiste, S. D. Weigand, *et al.*, “Age, sex, and apoe  $\epsilon$ 4 effects on memory, brain structure, and  $\beta$ -amyloid across the adult life span,” *JAMA neurology* **72**(5), 511–519 (2015).
- [31] H. Fonteijn, M. Modat, M. Clarkson, *et al.*, “An event-based model for disease progression and its application in familial Alzheimer’s disease and Huntington’s disease,” *NeuroImage* **60**(3), 1880–1889 (2012).
- [32] A. Young, N. Oxtoby, P. Daga, *et al.*, “A data-driven model of biomarker changes in sporadic Alzheimer’s disease,” *Brain* **137**(9), 2564–2577 (2014).
- [33] M. Lorenzi, M. Filippone, G. B. Frisoni, *et al.*, “Probabilistic disease progression modeling to characterize diagnostic uncertainty: application to staging and prediction in alzheimer’s disease,” *NeuroImage* **190**, 56–68 (2019).
- [34] C. Abi Nader, N. Ayache, P. Robert, *et al.*, “Monotonic gaussian process for spatio-temporal disease progression modeling in brain imaging data,” *Neuroimage* **205**, 116266 (2020).
- [35] R. Couronné, M. Louis, and S. Durrleman, “Longitudinal autoencoder for multi-modal disease progression modelling.” preprint (2019).
- [36] B. Sauty and S. Durrleman, “Progression models for imaging data with longitudinal variational auto encoders,” in *MICCAI 2022, International Conference on Medical Image Computing and Computer Assisted Intervention*, (2022).
- [37] K. Ito, B. Corrigan, Q. Zhao, *et al.*, “Disease progression model for cognitive deterioration from alzheimer’s disease neuroimaging initiative database,” *Alzheimer’s & Dementia* **7**(2), 151–160 (2011).
- [38] M. N. Samtani, M. Farnum, V. Lobanov, *et al.*, “An improved model for disease progression in patients from the alzheimer’s disease neuroimaging initiative,” *The Journal of Clinical Pharmacology* **52**(5), 629–644 (2012).
- [39] M. Bilgel, Y. An, A. Lang, *et al.*, “Trajectories of alzheimer disease-related cognitive measures in a longitudinal sample,” *Alzheimer’s & Dementia* **10**(6), 735–742 (2014).
- [40] B. Jedynak, A. Lang, B. Liu, *et al.*, “A computational neurodegenerative disease progression score: method and results with the Alzheimer’s disease neuroimaging initiative cohort,” *Neuroimage* **63**(3), 1478–1486 (2012).
- [41] J.-B. Schiratti, S. Allasonniere, O. Colliot, *et al.*, “Learning spatiotemporal trajectories from manifold-valued longitudinal data,” in *Neural Information Processing Systems*, (28) (2015).
- [42] I. Koval, J.-B. Schiratti, A. Routier, *et al.*, “Statistical learning of spatiotemporal patterns from longitudinal manifold-valued networks,” in *International Conference on MICCAI*, 451–459, Springer (2017).
- [43] L. L. Raket, “Statistical disease progression modeling in Alzheimer disease,” *Frontiers in big Data* **3** (2020).
- [44] J. L. Bernal-Rusiel, D. N. Greve, M. Reuter, *et al.*, “Statistical analysis of longitudinal neuroimage data with linear mixed effects models,” *Neuroimage* **66**, 249–260 (2013).
- [45] J. L. Bernal-Rusiel, M. Reuter, D. N. Greve, *et al.*, “Spatiotemporal linear mixed effects modeling for the mass-univariate analysis of longitudinal neuroimage data,” *Neuroimage* **81**, 358–370 (2013).

- [46] M. R. Sabuncu, J. L. Bernal-Rusiel, M. Reuter, *et al.*, “Event time analysis of longitudinal neuroimage data,” *NeuroImage* **97**, 9–18 (2014).
- [47] S. L. Risacher, L. Shen, J. D. West, *et al.*, “Longitudinal mri atrophy biomarkers: relationship to conversion in the adni cohort,” *Neurobiology of aging* **31**(8), 1401–1418 (2010).
- [48] N. J. Tustison, A. J. Holbrook, B. B. Avants, *et al.*, “Longitudinal mapping of cortical thickness measurements: An alzheimer’s disease neuroimaging initiative-based evaluation study,” *Journal of Alzheimer’s Disease* **71**(1), 165–183 (2019).
- [49] Y. Li, L. Zhang, A. Bozoki, *et al.*, “Early prediction of alzheimer’s disease using longitudinal volumetric mri data from adni,” *Health Services and Outcomes Research Methodology* **20**(1), 13–39 (2020).
- [50] X. Hua, D. P. Hibar, S. Lee, *et al.*, “Sex and age differences in atrophic rates: an adni study with n= 1368 mri scans,” *Neurobiology of aging* **31**(8), 1463–1480 (2010).
- [51] O. Sangha, D. Ma, K. Popuri, *et al.*, “Structural volume and cortical thickness differences between males and females in cognitively normal, cognitively impaired and alzheimer’s dementia population,” *Neurobiology of Aging* **106**, 1–11 (2021).
- [52] F. Cieri, X. Zhuang, D. Cordes, *et al.*, “Relationship of sex differences in cortical thickness and memory among cognitively healthy subjects and individuals with mild cognitive impairment and alzheimer disease,” *Alzheimer’s research & therapy* **14**(1), 1–12 (2022).
- [53] L. Gutiérrez-Galve, M. Lehmann, N. Z. Hobbs, *et al.*, “Patterns of cortical thickness according to apoe genotype in alzheimer’s disease,” *Dementia and geriatric cognitive disorders* **28**(5), 461–470 (2009).
- [54] S. Abushakra, A. P. Porsteinsson, M. Sabbagh, *et al.*, “Apoε4/ε4 homozygotes with early alzheimer’s disease show accelerated hippocampal atrophy and cortical thinning that correlates with cognitive decline,” *Alzheimer’s & Dementia: Translational Research & Clinical Interventions* **6**(1), e12117 (2020).
- [55] Y. Liu, J.-T. Yu, H.-F. Wang, *et al.*, “Apoε genotype and neuroimaging markers of alzheimer’s disease: systematic review and meta-analysis,” *Journal of Neurology, Neurosurgery & Psychiatry* **86**(2), 127–134 (2015).
- [56] B. Li, J. Shi, B. A. Gutman, *et al.*, “Influence of apoe genotype on hippocampal atrophy over time-an n= 1925 surface-based adni study,” *PloS one* **11**(4), e0152901 (2016).
- [57] J. Kim, S. Park, H. Yoo, *et al.*, “The impact of apoe 4 in alzheimer’s disease differs according to age,” *Journal of Alzheimer’s Disease* **61**(4), 1377–1385 (2018).
- [58] O. Hansson, J. Seibyl, E. Stomrud, *et al.*, “Csf biomarkers of alzheimer’s disease concord with amyloid-β pet and predict clinical progression: a study of fully automated immunoassays in biofinder and adni cohorts,” *Alzheimer’s & dementia* **14**(11), 1470–1481 (2018).
- [59] A. Routier, N. Burgos, M. Díaz, *et al.*, “Clinica: An open-source software platform for reproducible clinical neuroscience studies,” *Frontiers in Neuroinformatics* **15** (2021).
- [60] B. Fischl, “Freesurfer,” *NeuroImage* **62**(2), 774–781 (2012).
- [61] C. Destrieux, B. Fischl, A. Dale, *et al.*, “Automatic parcellation of human cortical gyri and sulci using standard anatomical nomenclature,” *NeuroImage* **53**(1), 1–15 (2010).
- [62] M. Lehmann, A. Douiri, L. G. Kim, *et al.*, “Atrophy patterns in alzheimer’s disease and semantic dementia: a comparison of freesurfer and manual volumetric measurements,” *NeuroImage* **49**(3), 2264–2274 (2010).
- [63] L. Clerx, H. Gronenschild, C. Echavarri, *et al.*, “Can freesurfer compete with manual volumetric measurements in alzheimer’s disease?,” *Current Alzheimer Research* **12**(4), 358–367 (2015).
- [64] N. Tzourio-Mazoyer, B. Landeau, D. Papathanassiou, *et al.*, “Automated anatomical labeling of activations in spm using a macroscopic anatomical parcellation of the mni mri single-subject brain,” *NeuroImage* **15**(1), 273–289 (2002).
- [65] E. Luders, K. L. Narr, P. M. Thompson, *et al.*, “Gender effects on cortical thickness and the influence of scaling,” *Human brain mapping* **27**(4), 314–324 (2006).
- [66] X. Chen, P. S. Sachdev, W. Wen, *et al.*, “Sex differences in regional gray matter in healthy individuals aged 44–48 years: a voxel-based morphometric study,” *NeuroImage* **36**(3), 691–699 (2007).

- [67] M. Lotze, M. Domin, F. H. Gerlach, *et al.*, “Novel findings from 2,838 adult brains on sex differences in gray matter brain volume,” *Scientific reports* **9**(1), 1–7 (2019).
- [68] X. Han, J. Jovicich, D. Salat, *et al.*, “Reliability of mri-derived measurements of human cerebral cortical thickness: the effects of field strength, scanner upgrade and manufacturer,” *Neuroimage* **32**(1), 180–194 (2006).
- [69] J.-B. Schiratti, S. Allasonniere, O. Colliot, *et al.*, “Learning spatiotemporal trajectories from manifold-valued longitudinal data,” in *Neural Information Processing Systems, Advances in Neural Information Processing Systems*, (Montréal, Canada) (2015).
- [70] I. Koval, J.-B. Schiratti, A. Routier, *et al.*, “Statistical learning of spatiotemporal patterns from longitudinal manifold-valued networks,” in *Medical Image Computing and Computer Assisted Intervention MICCAI 2017*, M. Descoteaux, L. Maier-Hein, A. Franz, *et al.*, Eds., 451–459, Springer International Publishing, (Cham) (2017).
- [71] E. Kuhn and M. Lavielle, “Coupling a stochastic approximation version of em with an mcmc procedure,” *ESAIM: Probability and Statistics* **8**, 115–131 (2004).
- [72] S. Allasonnière, E. Kuhn, and A. Trouvé, “Construction of bayesian deformable models via a stochastic approximation algorithm: a convergence study,” *Bernoulli* **16**(3), 641–678 (2010).
- [73] S. Gruffaz, P.-E. Poulet, E. Maheux, *et al.*, “Learning riemannian metric for disease progression modeling,” *Advances in Neural Information Processing Systems* **34** (2021).
- [74] B. Sauty and S. Durrleman, “Riemannian metric learning for progression modeling of longitudinal datasets,” in *ISBI 2022-International Symposium on Biomedical Imaging*, (2022).
- [75] Y. Benjamini and D. Yekutieli, “False discovery rate–adjusted multiple confidence intervals for selected parameters,” *Journal of the American Statistical Association* **100**(469), 71–81 (2005).
- [76] S. Derflinger, C. Sorg, C. Gaser, *et al.*, “Grey-matter atrophy in alzheimer’s disease is asymmetric but not lateralized,” *Journal of Alzheimer’s Disease* **25**(2), 347–357 (2011).
- [77] I. Koval, A. Bône, M. Louis, *et al.*, “Ad course map charts alzheimer’s disease progression,” *Scientific Reports* **11**(1), 1–16 (2021).
- [78] S. Gauthier, B. Reisberg, M. Zaudig, *et al.*, “Mild cognitive impairment,” *The lancet* **367**(9518), 1262–1270 (2006).
- [79] R. C. Petersen, “Mild cognitive impairment,” *CONTINUUM: Lifelong Learning in Neurology* **22**(2 Dementia), 404 (2016).
- [80] R. C. Petersen, P. Aisen, L. A. Beckett, *et al.*, “Alzheimer’s disease neuroimaging initiative (adni): clinical characterization,” *Neurology* **74**(3), 201–209 (2010).
- [81] J. L. Whitwell, W. R. Crum, H. C. Watt, *et al.*, “Normalization of cerebral volumes by use of intracranial volume: implications for longitudinal quantitative mr imaging,” *American journal of neuroradiology* **22**(8), 1483–1489 (2001).
- [82] E. Westman, C. Aguilar, J.-S. Muehlboeck, *et al.*, “Regional magnetic resonance imaging measures for multivariate analysis in alzheimer’s disease and mild cognitive impairment,” *Brain topography* **26**(1), 9–23 (2013).
- [83] O. Voevodskaya, A. Simmons, R. Nordenskjöld, *et al.*, “The effects of intracranial volume adjustment approaches on multiple regional mri volumes in healthy aging and alzheimer’s disease,” *Frontiers in aging neuroscience* **6**, 264 (2014).
- [84] Q. Zhou, M. Goryawala, M. Cabrerizo, *et al.*, “Significance of normalization on anatomical mri measures in predicting alzheimer’s disease,” *The Scientific World Journal* **2014** (2014).
- [85] C. M. Williams, H. Peyre, R. Toro, *et al.*, “Neuroanatomical norms in the uk biobank: The impact of allometric scaling, sex, and age,” *Human Brain Mapping* **42**(14), 4623–4642 (2021).
- [86] B. Sauty and S. Durrleman, “Impact of sex and apoe- $\epsilon$ 4 genotype on regional brain metabolism in alzheimer’s disease,” in *2023 IEEE 20th International Symposium on Biomedical Imaging (ISBI)*, (2023).