Diagnosis-Independent Alzheimer Disease Biomarker Signature in Cognitively Normal Elderly People

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Objective: To identify biomarker patterns typical for Alzheimer disease (AD) in an independent, unsupervised way, without using information on the clinical diagnosis.

Design: Mixture modeling approach.

Setting: Alzheimer’s Disease Neuroimaging Initiative database.

Patients or Other Participants: Cognitively normal persons, patients with AD, and individuals with mild cognitive impairment.

Main Outcome Measures: Cerebrospinal fluid–derived β-amyloid protein 1-42, total tau protein, and phosphorylated tau181P protein concentrations were used as biomarkers on a clinically well-characterized data set. The outcome of the qualification analysis was validated on 2 additional data sets, 1 of which was autopsy confirmed.

Results: Using the US Alzheimer’s Disease Neuroimaging Initiative data set, a cerebrospinal fluid β-amyloid protein 1-42/phosphorylated tau181P biomarker mixture model identified 1 feature linked to AD, while the other matched the “healthy” status. The AD signature was found in 90%, 72%, and 36% of patients in the AD, mild cognitive impairment, and cognitively normal groups, respectively. The cognitively normal group with the AD signature was enriched in apolipoprotein E ε4 allele carriers. Results were validated on 2 other data sets. In 1 study consisting of 68 autopsy-confirmed AD cases, 64 of 68 patients (94% sensitivity) were correctly classified with the AD feature. In another data set with patients (n=57) with mild cognitive impairment followed up for 5 years, the model showed a sensitivity of 100% in patients progressing to AD.

Conclusions: The mixture modeling approach, totally independent of clinical AD diagnosis, correctly classified patients with AD. The unexpected presence of the AD signature in more than one-third of cognitively normal subjects suggests that AD pathology is active and detectable earlier than has heretofore been envisioned.

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T HE INITIATION OF THE ALZHEIMER disease (AD) pathogenic process is typically unobserved and has been thought to precede the first symptoms by 10 years or more. Therefore, demonstrating that AD biomarkers, such as cerebrospinal fluid β-amyloid protein 1-42 (CSF Aβ1-42), total CSF tau protein, and CSF phosphorylated tau181P (P-Tau181P) protein concentrations,1 are true indicators of the pathogenic process at an early stage is a major challenge. Although other biomarkers determined in CSF or plasma can also be envisioned,2,3 P-Tau and Aβ biomarkers are currently already being considered for inclusion in revised AD diagnostic criteria.4

To date, assessment of biomarker accuracy relies on the clinical AD diagnosis as its point of reference. Early detection of AD is generally rephrased as predicting the progression from mild cognitive impairment (MCI) to AD. In this scenario, biomarker information obtained at the MCI stage is used to infer a future AD diagnosis, for instance, in a time-to-event analysis (with AD clinical diagnosis as the event) using Kaplan-Meier or Cox proportional hazards regression methods.1 Despite the conceptual simplicity of biomarker assessment, it is debatable whether the methods used truly assess to what extent biomarkers are indicators of the pathogenic process. One issue is the time lag between the

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pathogenic process and clinical diagnosis; the other confounding issue is errors in the clinical AD diagnosis. These issues are related to the use of clinical diagnosis as the point of reference for the pathogenic process, which can bias biomarker performance assessment and lead to suboptimal decisions criteria.

To circumvent or possibly remedy this situation, we applied an alternative unsupervised learning approach to biomarker assessment that does not use the clinical diagnosis as the point of reference. First, we illustrate the key ideas when applying a single biomarker in this way and then proceed to build a model for a multibiomarker setting. Finally, we validate the model obtained using independent data sets and discuss our results in view of future AD biomarker development and our current understanding of the AD pathogenic process.

### METHODS

**STUDY PARTICIPANTS AND DIAGNOSIS**

Detailed information on the patient population, including statements on appropriate approvals by the institutional review boards, is described in the original articles of the study. \(^1,^5,^6\) (Table 1).

**BIOMARKER DETERMINATIONS**

The CSF samples were analyzed for concentrations of Aβ1-42, total tau, and P-Tau\(_{181P}\) using the xMAP platform (Luminex Corp, Austin, Texas) and INNO-BIA AlzBio3 research-use-only reagents, as previously described. \(^6,^8\) Only subjects with a valid test result for all 3 biomarkers were included (Table 1). Apolipoprotein E (APOE) genotyping data were obtained on each subject.

**STATISTICAL ANALYSIS**

All data analysis was performed using R version 2.6.1. \(^9\) Two-component mixture models of normal distributions (single biomarker) or multivariate normal distributions (2 biomarkers) were fitted. \(^10\) Briefly, mixture modeling is a 2-step iterative process based on the expectation-maximization algorithm, under the model assumption that the data at hand are a mix sampled from 2 different normal distributions. For the individual data points, the originating distribution is unknown and is treated as a latent variable. In a first E (expectation) step, the latent class membership is estimated based on random parameter estimates for the originating distributions (2 means and 2 SDs for the single biomarker analysis). The latent class information is then used (M step) to calculate better parameter estimates for the originating distributions. The process is then iterated to convergence. \(^11\) Mixture modeling was finalized with a formal evaluation of the number of components that provided the best fit to the data. Classic receiver operating characteristic analysis was performed using the R package ROCR. \(^12\) The associations between the predicted AD feature group membership and either APOE genotype or follow-up diagnosis were addressed with \(\chi^2\) tests or an exact alternative where appropriate. In subjects with an AD feature, biomarker levels were compared using a general linear model.

Finally, recent FDA guidelines (http://www.fda.gov/downloads/medicalDevices/DeviceRegulationandGuidance/GuidanceDocuments/UCM071287.pdf) that have tried to ad-
address the issue of biased estimates of diagnostic performance recommend that the terms positive percentage of agreement and negative percentage of agreement be used instead of specificity and sensitivity in cases where no gold standard (nonreference standard) is available. In the present study, 2 data sets (US-ADNI and Swedish data set) were not autopsy confirmed, whereas 1 data set (Belgian data set) was. Given this mix, we have retained the conventional terms sensitivity and specificity to avoid confusion.

RESULTS

MIXTURE MODEL BUILDING BASED ON A SINGLE BIOMARKER (CSF Aβ1-42)

The unsupervised learning mixture modeling method simply assumes that the CSF Aβ1-42 data are obtained from 2 populations (eg, subjects with AD and healthy controls). To identify these latent subpopulations, we initially modeled the US-ADNI data set (normal, MCI, and AD) without using the group labels. As seen in Figure 1A, a bimodal, 2-component mixture distribution fit the actual data summarized in the histogram. The mixture distribution was dominated by the first component, which covered 68% of the population. A more detailed look at the mixture components (Figure 1B) revealed that these were clearly separated. With equal weight for both distributions, an optimal decision boundary was set at 188 pg/mL, with an overlap or incorrect classification rate of 3% on each side. Because the identified mixture components had no meaning as such, a validation step was required for biological interpretation. A straightforward approach was to assess the mixture proportions in the subject groups clinically diagnosed as being normal or having MCI or AD (Figure 2). In the AD subgroup, the mixture proportion of component 1 was 90%, strongly suggesting that this component can be considered as bearing the AD signature and thereby making component 2 the healthy signature. The AD signature mixture proportion was 73% and 39% in the MCI and normal groups, respectively. Using the mixture model, it was reasonable to select a cutoff value of 188 pg/mL, which in a classic receiver operating characteristic analysis (Figure 3) yielded 91% sensitivity (91
of 100) and 62% specificity (71 of 114). A straightforward selection of a decision criterion that balanced sensitivity and specificity by minimizing the difference between both performance characteristics yielded a cutoff value of 159 pg/mL, with 74% sensitivity (74 of 100) and 75% specificity (86 of 114).

EXTENDING THE MIXTURE MODEL FOR MULTIPLE BIOMARKERS

The simple mixture model outlined earlier can easily be extended to include multiple biomarkers. When applied this way, one then considers a mixture of multivariate normal distributions, with the multivariate dimension equal to the number of biomarkers (eg, bivariate normal for 2 biomarkers). Following earlier reports, we combined CSF β-amyloid 1–42 concentration with either CSF total tau and/or CSF P-Tau181P concentration, with both tau biomarkers log transformed before analysis to improve normality. The model fit, indicating Akaike Information Criterion (AIC) was 4137 for the combined CSF β1-42/CSF P-Tau181P mixture model and 4163 for the combined CSF β1-42/CSF total tau mixture model. With lower AIC values indicating a relatively better fit, this implies that a combined CSF β1-42/CSF P-Tau181P mixture model is the most adequate of the 2 combinations. In any case, both combined models are superior to the simple CSF β1-42 model that yielded an AIC of 4356. This was confirmed by tests for significance of regression coefficients in the combined CSF β1-42/CSF P-Tau181P mixture model (weighted generalized linear model fitted to each component with the posterior probabilities as weights). Highly significant contributions for both CSF β1-42 and CSF P-Tau181P in both components of the mixture model were found (all P values <.001). Future evaluation of the possible additional utility of a mixture model containing all 3 biomarkers should be performed on a data set containing subjects with different dementia diagnoses. To finalize the mixture modeling process, a combined CSF β1-42/CSF P-Tau181P mixture model was fitted to the data with the number of components ranging from 1 to 5. Again, AIC was applied to evaluate model fit and select the optimal number of components. The combined CSF β1-42/CSF P-Tau181P mixture model with 2 components revealed the lowest AIC (4138, 4139, and 4289 for 2 [CSF β1-42/CSF P-Tau181P], 3, and 1 [CSF β1-42] component, respectively) and was selected as the final mixture model.

The combined CSF β1-42/CSF P-Tau181P mixture model showed a mixture proportion of 66% and 34% for the 2 signatures in the complete data set. A breakdown of these signatures over the subject groups (Figure 4) revealed that signature 1 (red in Figure 4) can be considered the AD signature. On classifying subjects based on the combined CSF β1-42/CSF P-Tau181P mixture model, 41

![Figure 3](image-url)  
Figure 3. Receiver operating characteristic curve analysis for cerebrospinal fluid–derived β-amyloid protein 1–42 (CSF Aβ1-42)–based identification of Alzheimer disease (AD). Sensitivity ("true-positive rate") was assessed in the AD group, and specificity ("false-positive rate") was assessed in the normal group. AUC indicates area under the curve. Numbers with arrows indicate optimal decision boundaries (1) obtained with classic receiver operating characteristic analysis and minimizing the difference between sensitivity and specificity (159 pg/mL) and (2) between 2 components identified by unsupervised mixture modeling (188 pg/mL).

![Figure 4](image-url)  
Figure 4. A combined cerebrospinal fluid–derived β-amyloid protein 1–42 (CSF Aβ1-42)/CSF phosphorylated tau181P (CSF P-Tau181P) mixture model applied to the subject groups. Densities of each signature are represented with confidence ellipses, and signature membership of the subject based on the mixture is indicated with the corresponding color (signature 1 is the Alzheimer disease [AD] signature [red]; signature 2 is the healthy signature [green]). MCI indicates mild cognitive impairment.
of 114 normal subjects (36%) could be allocated to the AD signature, which also was found in 142 of 196 subjects with MCI (72%) and 90 of 100 subjects with AD (90%). This corresponds to classic sensitivity and specificity estimates of 90% and 64%, respectively.

These results indicate that the combined CSF Aβ1-42/CSF P-Tau181P mixture model (with better AIC) provides a similar decision as compared with the simple CSF Aβ1-42 mixture model. The lower AIC reflects a better separation between the 2 signatures in 2 dimensions (Figure 4) as compared with the single dimension (Figure 2), probably making the CSF Aβ1-42/CSF P-Tau181P approach more robust.

**VALIDATING THE SINGLE AND MULTIPLE MIXTURE MODELS**

Because of their essentially diagnosis-independent origin, mixture models are less sensitive to overfitting, making independent validation less of an issue. Nevertheless, we explored the validity of the CSF Aβ1-42 and CSF Aβ1-42/CSF P-Tau181P mixture models in 2 independent studies. For the sensitivity aspect, both mixture models showed a sensitivity of 57 of 57 subjects with MCI (100%) progressing to AD over the next 5 years (derived from Hansson et al1) (Figure 5A), while sensitivity for autopsy-confirmed cases5 was 63 of 68 (93%) and 64 of 68 (94%) for CSF Aβ1-42 and CSF Aβ1-42/CSF P-Tau181P mixture models, respectively (Figure 5B). From the 4 misclassifications in the latter study, 1 was completely in the center of the control feature, whereas 3 were results that were not likely to belong to either the AD or the healthy feature. Both of these data sets included a population with slightly lower CSF Aβ1-42 levels and higher CSF P-Tau181P levels as compared with the typical AD signature in the ADNI data.

In addition, we investigated the relation between the CSF Aβ1-42/CSF P-Tau181P mixture model and the diagnostic evolution (Table 2). Although there were few differences between follow-up diagnosis and baseline diagnosis in this short (mostly 1-year) follow-up period, there was a tendency for more progression to MCI in cognitively normal

<table>
<thead>
<tr>
<th>Diagnosis at Baseline</th>
<th>Mixture Model Classification</th>
<th>Latest Follow-up Diagnosis, No. (%)</th>
<th>P Value for Association</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal</td>
<td>AD</td>
<td>37 (91) 3 (8) 0</td>
<td>.13</td>
</tr>
<tr>
<td>MCI</td>
<td>Healthy</td>
<td>71 (99) 1 (1) 0</td>
<td>.04</td>
</tr>
<tr>
<td>AD</td>
<td>AD</td>
<td>2 (1) 100 (73) 35 (26)</td>
<td>.99</td>
</tr>
<tr>
<td>AD</td>
<td>Healthy</td>
<td>3 (6) 42 (82) 6 (12)</td>
<td>.99</td>
</tr>
<tr>
<td>AD</td>
<td>Healthy</td>
<td>0 0 88 (100)</td>
<td>.99</td>
</tr>
</tbody>
</table>

subjects with the AD feature as compared with cognitively normal subjects with the healthy feature (P = .13). Subjects with MCI with the AD feature were more likely to progress to AD and less likely to regress to cognitively normal as compared with subjects with MCI with the healthy feature (P = .04). In all cases, the evolution observed was consistent with the mixture model classification.

CHARACTERIZING COGNITIVELY NORMAL SUBJECTS WITH AN AD FEATURE

To better understand the 36% of cognitively normal subjects who had the CSF Aβ1-42/CSF P-Tau181P mixture model AD feature (Figure 4), this subpopulation was characterized in more detail. With respect to common risk factors, there was no evidence for differences between cognitively normal subjects with the AD feature or healthy feature for age (P = .17, t test), Mini-Mental State Examination score (P = .51, t test), or sex (P = .92; Fisher exact test). However, there was a clear association (Table 3) between mixture model feature and APOE genotype in cognitively normal subjects (P < .001, Fisher exact test), with the odds for having an APOE ε4 allele in the AD cluster being 6.88 times (95% confidence interval, 2.46-20.92) the odds for having an APOE ε4 allele in the non-AD cluster. In other words, the population of cognitively normal individuals classified as having an AD biomarker signature was significantly enriched in APOE ε4 carriers. In addition, a comparison of CSF Aβ1-42 and CSF P-Tau181P biomarker levels between cognitively normal subjects and subjects with MCI and AD having the AD mixture model feature revealed no evidence for differences between the diagnostic groups for CSF Aβ1-42 (P = .17) but a clear difference (P < .001) for CSF P-Tau181P.

Contrasting the clinical diagnosis group averages (for subjects with the AD feature) with the mixture model averages (Table 4) revealed that the CSF Aβ1-42 component was nearly complete (reaching AD feature average) in cognitively normal subjects, while the CSF P-Tau181P component was roughly halfway between the healthy and AD stage.

### Table 3. Association Between Mixture Model Classification and APOE Genotype in Normal Subjects From the US-ADNI Study

<table>
<thead>
<tr>
<th>APOE Genotype, Count (%)</th>
<th>1 or 2 ε4 Alleles</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cluster</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AD</td>
<td>22 (54)</td>
<td>41</td>
</tr>
<tr>
<td>Non-AD</td>
<td>65 (89)</td>
<td>73</td>
</tr>
<tr>
<td>Total</td>
<td>87</td>
<td>114</td>
</tr>
</tbody>
</table>


*More detailed information on the study population is described in Shaw et al.*

### Table 4. CSF Aβ1-42 and CSF P-Tau181P Biomarker Levels in Subjects With the AD Mixture Model Feature Contrasted With the Mean Values of the Mixture Model Feature

<table>
<thead>
<tr>
<th>Mean (% AD Trajectory), pg/mL</th>
</tr>
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<tbody>
<tr>
<td>Clinical Diagnosis Group for Subjects With AD Feature</td>
</tr>
<tr>
<td>-----------------------------</td>
</tr>
<tr>
<td>CSF Aβ1-42 concentration</td>
</tr>
<tr>
<td>CSF P-Tau181P Concentration (log transformed)</td>
</tr>
</tbody>
</table>

*Abbreviations: AD, Alzheimer disease; CSF Aβ1-42, cerebrospinal fluid–derived β-amyloid protein 1-42; CSF P-Tau181P, cerebrospinal fluid–derived phosphorylated tau181P.*
to have higher CSF P-Tau/H9252 levels as compared with the AD signature in the ADNI population. This finding is consistent with an observed CSF P-Tau181P level increase during cognitive decline and dementia. It also suggests an intrinsically different role for the 2 biomarkers in the mixture model, with CSF Aβ1-42 as an initial marker and CSF P-Tau181P as a subsequent stage marker related to dementia symptoms and disease progression. This could also imply that CSF Aβ1-42 is the initial driver of AD pathology and that changes in CSF total tau and/or CSF P-Tau181P concentrations are a secondary effect, although other interpretations are possible since CSF tau concentration is not elevated in all neurodegenerative tauopathies. The view that Aβ1-42 changes occur earlier than tau pathology is further corroborated by (1) follow-up studies showing that reduction of CSF Aβ1-42 concentration predicts cognitive decline and incident dementia in healthy elderly individuals before observed increases in CSF total tau or CSF P-Tau181P concentrations, (2) genetic data showing that polymorphisms in the tau-encoding MAPT gene influence CSF tau levels only in individuals with low CSF Aβ1-42 concentration, and (3) repeated Pittsburgh Compound B positron emission tomography on patients with AD showed no increased amyloid load in the brain with time.

A salient outcome of the mixture modeling approach is the presence of an AD signature in more than one-third of cognitively normal subjects (39% based on CSF Aβ1-42 concentration only; 36% based on the combined model). This is not surprising because many neuropathological studies on cognitively normal elderly individuals reveal that a large portion of healthy elderly individuals exhibit amyloid-containing plaques and tau-containing neurofibrillary tangles in their brains. Moreover, Pittsburgh Compound B positron emission tomography studies show that many healthy elderly controls also exhibit increased Aβ levels in their brains. Furthermore, this finding is directly supported by the enrichment of APOE ε4 carriers, a well-characterized risk factor for AD. It also reflects the documented decline of CSF Aβ1-42 concentration with age in cognitively normal APOE ε4 carriers and underscores the presence of AD pathology before the onset of symptoms. Nevertheless, such findings will need to be confirmed in subsequent studies that include cognitively normal subjects who can be followed up for possibly 10 years or more.

In summary, the analytical approach reported herein demonstrates that mixture modeling provides valuable insights for biomarker assessment in the field of AD. The unsupervised learning method that downplays the clinical diagnosis paints a different picture than clinical diagnostic methods and suggests that AD pathology is active considerably earlier than has heretofore been envisioned. Thus, taken together, these data provide further support for the view that revision of current diagnostic criteria for AD is needed, or at least as far as early-stage AD is concerned.

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Additional Contributions: We thank the ADNI colleagues for contributions to the work summarized herein.

REFERENCES


5. Engellbohrs S, De Vreese K, Van de Casteele T, et al. Diagnostic performance of...


