Mixed effect models for longitudinal responses with different types of dropout: an application to the Leiden 85-plus study. Supplementary material

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1 Simulation study

A simulation study has been carried out to investigate the following points: for the longitudinal model, the focus is on the dependence between the baseline and subsequent responses. For the pattern mixture model, we investigate whether S_i and/or the dropout type may be used to summarize participation in the study. We define three simulation settings to study the robustness of the proposed model with respect to:

- the validity of the approximation for the baseline-specific latent effects in equation (6) of the manuscript, (setting 1);

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- the performance of the partially shared random effect structure in modeling the dependence between baseline and subsequent responses, (setting 2);
- the performance of the proposed pattern mixture model as a tool for sensitivity analysis, (setting 3).

In the following, we will give a brief description of the simulation design.

1.1 Setting 1

To study the proposed approximation of ϕ_i through a linear function of y_{i1} , we have drawn 100 samples according to the assumptions below:

$$\begin{aligned}
Y_{it} | \mathbf{b}_i, \phi_i &\sim \text{Bin}(30; \pi_{it}) \\
\text{logit}(\pi_{it}) &= \mathbf{x}'_{it} \boldsymbol{\beta} + b_i + \alpha \phi_i \quad t = 2, \dots, T \\
&\text{and} \\
\text{logit}(\pi_{i1}) &= \mathbf{x}'_{i1} \boldsymbol{\beta} + b_i + \phi_i \quad t = 1
\end{aligned}$$

The sample size is $n = 600$, and the number of occasions is $T = 6$, as in the Leiden 85+ study. Values for $\boldsymbol{\beta}$ have been chosen according to the baseline model estimates, see model (B) in Table 1 of the manuscript, while $\alpha = 0.10$. The covariates $\mathbf{x}_i$ have been drawn from the Leiden 85+ study data, while the latent effects are realizations of independent Gaussian random variables:

$$\begin{aligned}
b_i &\sim N(0, \sigma_b^2), & \sigma_b^2 &= 0.97^2 \\
\phi_i &\sim N(0, \sigma_\phi^2), & \sigma_\phi^2 &= 0.71^2
\end{aligned}$$

The missing data mechanism has been simulated according to a (conditional) Bernoulli distribution, where the parameter p_{it} represents the probability of the i -th unit being observed at the t -th visit:

$$p_{it} = \Pr(R_{it} = 1) = \frac{\exp(\eta_{it})}{1 + \exp(\eta_{it})}$$

where

$$\begin{aligned}
\eta_{it} &= \zeta_0 \mathbf{x}_{it} + \zeta_1 y_{t-1} \\
&= -1.3 - 0.76 \text{Age}_{it} - 0.07 \text{Gender}_i - 0.23 \text{Educ}_i - 0.35 \text{APOE}_{34-44i} \\
&+ 0.07 \text{MMSE}_{it-1}
\end{aligned}$$

That is a MAR scenario. We estimated model (6) in the manuscript, where $\alpha\phi_i$ is approximated by a linear function in y_{i1} .

1.2 Setting 2

We consider the baseline score as a dependent variable in post baseline model to approximate the influence of baseline-specific random intercept. Therefore, it could be interesting to verify the robustness of the proposed model when a simple variance component model holds, that is $\sigma_\phi = 0$, or when the baseline-specific random intercept does not influence post baseline responses, that is $\alpha = 0$. For this purpose, we have defined two scenarios under a MAR mechanism. We have drawn 100 samples according to the following scheme:

$$\begin{aligned}
Y_{it} | \mathbf{b}_i &\sim \text{Bin}(30; \pi_{it}) \\
\text{logit}(\pi_{it}) &= \mathbf{x}'_{it} \boldsymbol{\beta}^* + b_i \quad t = 2, \dots, T \\
&\text{and} \\
\text{scenario A} \quad \text{logit}(\pi_{i1}) &= \mathbf{x}'_{i1} \boldsymbol{\beta} + b_i \quad t = 1 \\
&\text{or} \\
\text{scenario B} \quad \text{logit}(\pi_{i1}) &= \mathbf{x}'_{i1} \boldsymbol{\beta} + b_i + \phi_i \quad t = 1
\end{aligned}$$

The sample size is $n = 600$, and the number of occasions is $T = 6$. Values for $\boldsymbol{\beta}^*$, $\boldsymbol{\beta}$, σ_b^2 , and σ_ϕ^2 have been defined according to estimates in Table 1, model (B). The missing data are generated according to the MAR model discussed in section 1.1.

1.3 Setting 3

To study the behaviour of the proposed pattern mixture models under different missing data mechanisms, we have drawn 100 samples according to the following scheme:

$$\begin{aligned} Y_{it} | \mathbf{b}_i, y_{i1} &\sim \text{Bin}(30; \pi_{it}) \\ \text{logit}(\pi_{it}) &= \mathbf{x}_{it}^\top \boldsymbol{\beta}^* + b_i + \alpha y_{i1} \quad t = 2, \dots, T \\ \text{logit}(\pi_{i1}) &= \mathbf{x}_{i1}^\top \boldsymbol{\beta} + b_i + \phi_i \quad t = 1 \end{aligned}$$

The sample size is $n = 600$, and the number of occasions is $T = 6$. Values for $\boldsymbol{\beta}^*$, $\boldsymbol{\beta}$, σ_b^2 , and σ_ϕ^2 have been defined as in section 1.1 above. For the missing data process, the following scenarios have been considered:

Ignorable dropout

- Scenario A: MCAR

$$\begin{aligned} \eta_{it} &= \mathbf{x}_{it}' \boldsymbol{\zeta}_0 \\ &= -1.3 - 0.76 \text{Age}_{it} - 0.07 \text{Gender}_i - 0.23 \text{Educ}_i - 0.35 \text{APOE}_{34-44i} \end{aligned}$$

- Scenario B: MAR

$$\begin{aligned} \eta_{it} &= \mathbf{x}_{it}' \boldsymbol{\zeta}_0 + \zeta_1 y_{t-1} \\ &= -1.3 - 0.76 \text{Age}_{it} - 0.07 \text{Gender}_i - 0.23 \text{Educ}_i - 0.35 \text{APOE}_{34-44i} \\ &\quad + 0.07 \text{MMSE}_{it-1} \end{aligned}$$

Non ignorable dropout

- Scenario C: Current response model

$$\begin{aligned} \eta_{it} &= \mathbf{x}_{it}' \boldsymbol{\zeta}_0 + \zeta_1 y_{it} \\ &= -1.3 - 0.76 \text{Age}_{it} - 0.07 \text{Gender}_i - 0.23 \text{Educ}_i - 0.35 \text{APOE}_{34-44i} \\ &\quad + 0.07 \text{MMSE}_{it} \end{aligned}$$

- Scenario D: Shared parameter model

$$\begin{aligned}
\eta_{it} &= \mathbf{x}_{it}'\boldsymbol{\zeta}_0 + b_i \\
&= -1.3 - 0.76Age_{it} - 0.07Gender_i - 0.23Educ_i - 0.35APOE_{34-44i} \\
&\quad + b_i
\end{aligned}$$

- Scenario E: Current response model with competing risks

$$\begin{aligned}
\eta_{it} &= \mathbf{x}_{it}'\boldsymbol{\zeta}_0 + \zeta_1 y_t \\
&= -1.3 - 0.76Age_{it} - 0.07Gender_i - 0.23Educ_i - 0.35APOE_{34-44i} \\
&\quad + 0.07MMSE_{it} \\
C_i &\sim Weibull(\exp(1.2 \times age), 8) \\
S_i^* &= \min(S_i, C_i)
\end{aligned}$$

In scenario E, we have defined two types of dropout, mimicking the couple (death, non participation) we have observed in the Leiden 85+ study. For this purpose, we assume that the censoring time C_i follows a Weibull distribution, where the shape parameter depends on age and the scale parameter is fixed. If $C_i < \min(S_i, T)$, then $\Delta_i = 1$ (death); while if $S_i < \min(C_i, T)$, we have $\Delta_i = 2$ (dropout). Obviously, $\Delta_i = 0$ for those completing the study.

1.4 Simulation results

1.5 Setting 1

Table 1 contains the results when data are generated through a variance component model with individual-specific latent effects accounting for the selection when entering the study. The adopted linear approximation slightly influences the parameter estimates of the fixed covariates in the model for post-baseline responses. In particular, the effect of *Educ* and *APOE*(34–44) is significant in the baseline and the post-baseline models, but the magnitude of the estimated effects in the post-baseline model is smaller when compared to the estimates in the baseline response model and to the true values. This

difference clearly represents the effect of the $(1 - \alpha)$ multiplier in $\beta^* = (1 - \alpha)\beta$. The estimated variance of the baseline-specific random effect $\hat{\sigma}_\phi^2$ is lower than the estimated variance for the random effects at subsequent occasions and both values are consistent with the true ones. This confirms the validity of the approximation of ϕ_i by the conditional mean $E(\phi_i | y_{i1})$, as a linear function in Y_{i1} .

1.6 Setting 2

Table 2 shows the parameter estimates obtained by fitting the proposed combined random intercept model when data are generated by a simple variance component model. The results show that parameter and random intercept variance estimates are quite close to the true values as the effect of MMSE₈₅ does. In scenario (A) when the component that represents the baseline specific heterogeneity at study entrance ϕ_i is not present, the corresponding variability estimate is close to zero. This confirms that the proposed model lead to estimates that are consistent with the values used for the data generating process.

1.7 Setting 3

For each scenario, we fitted a MAR and a PM model to investigate the ability of the latter to denote potential sensitivity of parameter estimates through interaction of S_i (scenario A-D) and S_i and Δ_i (scenario E) with observed covariates. Tables 3-7 present the results.

Under scenario A (Table 3), parameter and random effect variance estimates obtained by ignoring the missing data mechanism are close to the true values and the empirical significance is coherent with the data generating process. Looking at the PM model estimates, the effects of s_i and its interaction with age and other variables are significant only in a very small number of cases, which is coherent with the nominal size (0.05). So, in this case, the

PM model does correctly recognize the missing data process is ignorable.

Under scenario B (Table 4), parameter estimates obtained by fitting the MAR model are close to the true values as well; however, the PM estimates seem to underline significant effects of s and, less often, of $age \times s$. This is probably due to the presence of Y_{it-1} in the model for the missing data mechanism; this term depends on the individual random intercept and its effect may be misinterpreted as a non ignorable missing data mechanism. This highlights that borders between ignorable and non ignorable dropout models are not that clearly marked.

Under scenario C, see Table 5, we may notice that parameter estimates for the MAR model suffer from some bias; this is true, in particular, for the intercept and the age effect estimates. This is coherent with results obtained by fitting the PM model where the estimates for the effects of s and $s \times age$ are significant in a large proportion of samples. In this case, the PM model correctly recognizes the nature and the effects of the missing data mechanism on the longitudinal outcome.

Under scenario D, (see table 6), we may notice that parameter estimates for the MAR model are quite close to the true ones, but for the intercept, age and (to a lower extent) $Educ$ and σ_ϕ^2 . In this case, the missing data mechanism shares the same random effects of the longitudinal outcome; since the random effects account for omitted covariates which are supposed to be orthogonal to the observed ones, we would expect that only the intercept estimate be influenced by missing data. In this case, the PM model shows a significant s effect (coherent with the *true* missing data mechanism) and a lower proportion of samples where the interaction $age \times s$ is significant, the proportion being smaller than in scenario B above.

Under scenario E, (see Table 7), the parameter estimates for the MAR model seem to be substantially biased; the significant effect of the dropout pattern (summarized by s and δ) seem to suggest the presence of a NI missing data process. An interesting aspect of this scenario regards the different information that the dropout type provides: looking at the interaction of

dropout type with covariates, we found that the interaction with age is significant only for Δ_1 , corresponding to a dropout due to death. The PM model with dropout type shows a better performance when compared to the PM model based on S only, even if we may observe an unexpected high proportion of samples where interaction $APOE_{22-23} \times \Delta_2$ (ie drop-out due to non participation) is significant, possibly due to a limited sample size.

The results obtained (all scenarios) suggest that ignoring the dropout mechanism could lead to wrong conclusions and that PM models, even if not completely satisfactory, may represent a reliable screening tool to build a more complex model to handle non ignorable missing data.

Table 1: Setting 1; effects of baseline-specific random effect approximations, $\alpha = 0.1$

Variable	True	Mean	Median	sd
Cons.	-0.43	-1.11	-0.45	0.18
Age	-0.19	-0.19	-0.19	0.01
Gender	0	-0.01	-0.01	0.09
Educ.	1.06	0.96	1.03	0.09
APOE ₍₂₂₋₂₃₎	0	-0.02	-0.01	0.11
APOE ₍₂₄₎	0	-0.01	0.01	0.28
APOE ₍₃₄₋₄₄₎	-0.77	-0.67	-0.72	0.11
MMSE ₈₅	0	0.04	0.02	0.01
Cons _{bas}	1.98	3.06	2.46	0.17
Gender _{bas}	0	0.00	0.01	0.12
Educ _{bas}	1.06	1.04	1.05	0.12
APOE _{(22-23)bas}	0	-0.01	0.01	0.15
APOE _{(24)bas}	0	0.01	-0.00	0.39
APOE _{(34-44)bas}	-0.77	-0.74	-0.74	0.14
σ_b^2	0.941	0.957	1.034	
σ_ϕ^2	0.504	0.844	0.500	

Table 2: Setting 2. Random effect structure misspecification

Variable	True value	Scenario A			Scenario B		
		Mean	Median	sd	Mean	Median	sd
Cons.	-0.43	-0.61	-0.47	0.17	-0.64	-0.26	0.16
Age	-0.19	-0.19	-0.19	0.01	-0.19	-0.19	0.01
Gender	0	0.01	0.01	0.09	-0.01	-0.01	0.09
Educ.	0.69	0.68	0.69	0.09	0.65	0.68	0.09
APOE ₍₂₂₋₂₃₎	0	0.02	0.02	0.11	0.01	0.01	0.11
APOE ₍₂₄₎	0	0.09	0.13	0.27	0.06	0.05	0.27
APOE ₍₃₄₋₄₄₎	-0.46	-0.44	-0.45	0.10	-0.44	-0.48	0.11
MMSE ₈₅	0	0.01	0.01	0.01	0.01	-0.01	0.01
Cons _{bas}	1.98	2.57	2.44	0.15	2.60	2.22	0.16
Gender _{bas}	0	0.01	0.0	0.10	-0.02	-0.04	0.12
EduC _{bas}	1.06	1.07	1.06	0.10	1.05	1.04	0.12
APOE _{(22-23)bas}	0	0.02	0.02	0.12	0.02	0.01	0.15
APOE _{(24)bas}	0	0.08	0.09	0.31	0.08	0.11	0.37
APOE _{(34-44)bas}	-0.77	-0.77	-0.77	0.11	-0.76	-0.77	0.14
σ_b^2	0.941	0.912	0.904		0.927	0.959	
σ_ϕ^2	0	0.058	0.00				
σ_ϕ^2	0.504				0.632	0.433	

Table 3: Setting 3, scenario A: parameter estimates for the marginal (MAR) and the conditional (PM) models

Variable	True value	MAR				MNAR (PM)			
		Mean	Median	sd	%sig	Mean	Median	sd	%sig
Cons.	-0.43	-0.613	-0.236	0.178	54	-0.833	-0.315	0.245	51
Age	-0.19	-0.188	-0.187	0.010	100	-0.193	-0.192	0.668	81
Gender	0	-0.001	0.002	0.097	6	-0.020	-0.017	0.260	8
Educ.	0.69	0.675	0.714	0.099	98	0.648	0.655	0.270	66
APOE ₍₂₂₋₂₃₎	0	-0.003	-0.016	0.122	8	0.017	-0.002	0.341	7
APOE ₍₂₄₎	0	0.052	0.015	0.308	5	0.338	0.194	0.932	8
APOE ₍₃₄₋₄₄₎	-0.46	-0.429	-0.471	0.115	87	-0.367	-0.421	0.290	28
MMSE ₈₅	0.09	0.096	0.082	0.007	100	0.104	0.084	0.007	100
s						0.007	0.006	0.038	2
Cons _{bas}	1.98	2.571	2.211	0.172	100	2.731	2.248	0.174	100
Gender _{bas}	0	0.001	0.014	0.125	2	0.003	0.018	0.125	2
Educ _{bas}	1.06	1.066	1.067	0.127	100	1.051	1.062	0.127	100
APOE _{(22-23)bas}	0	0.003	-0.015	0.156	6	0.015	0.002	0.159	6
APOE _{(24)bas}	0	0.121	0.088	0.406	4	0.129	0.094	0.407	2
APOE _{(34-44)bas}	-0.77	-0.773	-0.802	0.144	100	-0.767	-0.790	0.145	100
Age*s						0.001	0.001	0.012	7
Gender*s						0.005	0.004	0.055	8
Educ*s						-0.000	0.000	0.057	8
APOE ₍₂₂₋₂₃₎ * s						-0.001	0.006	0.069	8
APOE ₍₂₄₎ * s						-0.060	-0.028	0.194	10
APOE ₍₃₄₋₄₄₎ * s						-0.007	0.000	0.061	5
σ_b^2	0.941	0.912	0.938			0.890	0.908		
σ_ϕ^2	0.504	0.652	0.417			0.789	0.414		

Table 4: Setting 3, scenario B: parameter estimates for the marginal (MAR) and the conditional (PM) models

Variable	True value	MAR				MNAR (PM)			
		Mean	Median	se	%sig	Mean	Median	se	%sig
Cons.	-0.43	-0.446	-0.148	0.193	45	-1.768	-1.236	0.238	97
Age	-0.19	-0.188	-0.188	0.011	100	-0.275	-0.296	0.066	83
Gender	0	0.007	0.011	0.098	6	0.069	0.056	0.237	6
Educ.	0.69	0.668	0.695	0.098	99	0.776	0.862	0.253	75
APOE ₍₂₂₋₂₃₎	0	-0.026	-0.040	0.122	4	0.074	0.060	0.309	9
APOE ₍₂₄₎	0	-0.005	-0.015	0.309	6	0.118	0.163	0.863	9
APOE ₍₃₄₋₄₄₎	-0.46	-0.478	-0.518	0.116	91	-0.313	-0.410	0.259	39
MMSE ₈₅	0.09	0.090	0.082	0.007	100	0.086	0.065	0.007	100
s						0.338	0.336	0.035	100
Cons _{bas}	1.98	2.409	2.153	0.186	100	2.279	1.741	0.188	100
Gender _{bas}	0	-0.015	-0.021	0.125	2	0.008	0.016	0.116	6
Educ _{bas}	1.06	1.045	1.044	0.127	100	0.931	0.914	0.118	100
APOE _{(22-23)bas}	0	-0.007	-0.012	0.158	6	-0.004	-0.010	0.147	1
APOE _{(24)bas}	0	0.002	-0.027	0.399	4	0.009	0.003	0.375	3
APOE _{(34-44)bas}	-0.77	-0.777	-0.779	0.143	100	-0.542	-0.562	0.149	92
Age*s						0.013	0.017	0.012	44
Gender*s						-0.010	-0.010	0.049	4
Educ*s						-0.043	-0.044	0.052	14
APOE ₍₂₂₋₂₃₎ * s						-0.020	-0.014	0.063	10
APOE ₍₂₄₎ * s						-0.022	-0.009	0.182	9
APOE ₍₃₄₋₄₄₎ * s						0.013	0.018	0.056	11
σ_b^2	0.941	0.945	0.966			0.767	0.785		
σ_ϕ^2	0.504	0.598	0.409			0.757	0.328		

Table 5: Setting 3, scenario C: parameter estimates for the marginal (MAR) and the conditional (PM) models

Variable	True value	MAR				MNAR (PM)			
		Mean	Median	se	%sig	Mean	Median	se	%sig
Cons.	-0.43	0.552	1.028	0.217	96	-0.702	-0.476	0.240	54
Age	-0.19	-0.137	-0.137	0.013	100	-0.151	-0.152	0.070	55
Gender	0	-0.005	-0.007	0.105	7	-0.005	-0.030	0.217	6
Educ.	0.69	0.757	0.794	0.106	99	0.806	0.792	0.230	87
APOE ₍₂₂₋₂₃₎	0	0.026	0.038	0.132	4	-0.047	-0.031	0.275	9
APOE ₍₂₄₎	0	0.091	0.087	0.335	6	0.083	0.143	0.807	8
APOE ₍₃₄₋₄₄₎	-0.46	-0.492	-0.519	0.126	87	-0.352	-0.375	0.244	47
MMSE ₈₅	0.09	0.050	0.0315	0.008	76	0.034	0.024	0.008	74
s						0.434	0.438	0.030	100
Cons _{bas}	1.98	1.398	0.964	0.206	86	1.036	0.812	0.212	81
Gender _{bas}	0	-0.018	-0.011	0.122	11	-0.000	0.002	0.105	11
Educ _{bas}	1.06	1.036	1.018	0.124	100	0.805	0.782	0.108	100
APOE(22-23)bas	0	0.025	0.028	0.155	5	-0.003	-0.005	0.134	4
APOE(24)bas	0	0.054	0.047	0.398	6	0.020	0.013	0.340	5
APOE(34-44)bas	-0.77	-0.741	-0.740	0.141	100	-0.412	-0.403	0.122	92
Age * s						0.012	0.012	0.013	85
Gender * s						0.004	0.008	0.047	7
Educ * s						-0.052	-0.053	0.049	21
APOE(22-23) * s						0.012	0.014	0.059	7
APOE(24) * s						-0.004	-0.029	0.174	9
APOE(34-44) * s						0.036	0.036	0.057	16
σ_b^2	0.941	1.050	1.122			0.694	0.705		
σ_ϕ^2	0.504	0.419	0.185			0.340	0.159		

Table 6: Setting 3, scenario D: parameter estimates for the marginal (MAR) and the conditional (PM) models

Variable	True value	MAR				MNAR (PM)			
		Mean	Median	se	%sig	Mean	Median	se	%sig
Cons.	-0.43	0.207	0.432	0.206	65	-1.721	-1.389	0.231	87
Age	-0.19	-0.149	-0.151	0.017	100	-0.244	-0.235	0.079	80
Gender	0	0.004	0.029	0.108	1	0.038	0.042	0.220	9
Educ.	0.69	0.812	0.833	0.110	100	0.641	0.718	0.236	71
APOE ₍₂₂₋₂₃₎	0	-0.003	0.001	0.136	1	-0.053	-0.044	0.282	9
APOE ₍₂₄₎	0	-0.003	0.008	0.344	9	-0.053	-0.097	0.760	8
APOE ₍₃₄₋₄₄₎	-0.46	-0.521	0.512	0.128	96	-0.331	-0.369	0.256	38
MMSE ₈₅	0.09	0.065	0.055	0.008	100	0.095	0.080	0.008	100
s						0.346	0.345	0.033	100
Cons.bas	1.98	1.748	1.535	0.195	100	2.495	2.115	0.206	100
Gender.bas	0	0.020	0.023	0.124	6	0.035	0.018	0.113	3
Educ.bas	1.06	1.040	1.034	0.125	100	1.091	1.086	0.116	100
APOE _{(22-23)bas}	0	-0.001	-0.000	0.157	4	-0.015	-0.025	0.144	7
APOE _{(24)bas}	0	-0.002	-0.010	0.397	5	-0.010	-0.021	0.366	3
APOE _{(34-44)bas}	-0.77	-0.760	-0.768	0.142	100	-0.641	-0.642	0.130	98
Age*s						0.010	0.011	0.015	23
Gender*s						-0.002	-0.006	0.055	9
Educ*s						0.026	0.032	0.058	5
APOE ₍₂₂₋₂₃₎ * s						0.012	0.005	0.068	6
APOE ₍₂₄₎ * s						0.018	0.014	0.190	7
APOE ₍₃₄₋₄₄₎ * s						0.004	0.009	0.063	7
σ_b^2	0.941	1.063	1.090			0.675	0.714		
σ_ϕ^2	0.504	0.383	0.251			0.807	0.389		

Table 7: Setting 3, scenario E: parameter estimates for the marginal (MAR) and the conditional (PM) models

Variable	True value	MAR				MNAR (PM1)				MNAR (PM2)			
		Mean	Median	se	%sig	Mean	Median	se	%sig	Mean	Median	se	%sig
Cons.	-0.43	0.728	1.138	0.229	99	-0.098	0.034	0.279	33	1.240	1.937	0.277	100
Age	-0.19	-0.140	-0.142	0.015	100	-0.171	-0.167	0.098	58	-0.172	-0.170	0.023	100
Gender	0	-0.004	0.010	0.111	7	-0.076	-0.090	0.241	5	0.022	0.019	0.203	7
Educ.	0.69	0.770	0.826	0.111	97	0.870	0.883	0.250	94	0.521	0.542	0.200	73
<i>MMSE</i> ₈₅	0.09	0.044	0.028	0.008	77	0.029	0.025	0.010	70	0.058	0.033	0.009	83
<i>APOE</i> ₍₂₂₋₂₃₎	0	0.006	0.011	0.139	2	-0.026	-0.038	0.297	5	-0.005	-0.016	0.240	1
<i>APOE</i> ₍₂₄₎	0	-0.028	-0.039	0.351	4	0.056	0.107	0.886	9	0.169	0.226	0.620	7
<i>APOE</i> ₍₃₄₋₄₄₎	-0.46	-0.509	-0.551	0.133	87	-0.479	-0.507	0.291	46	-0.244	-0.237	0.319	16
Cons.bas	1.98	1.238	0.827	0.216	87	0.916	0.805	0.255	76	1.606	0.995	0.221	90
Gender.bas	0	0.003	-0.002	0.123	6	0.008	0.011	0.110	6	0.005	-0.009	0.117	4
Educ.bas	1.06	1.027	1.025	0.124	100	0.899	0.905	0.112	100	0.953	0.942	0.119	100
<i>APOE</i> ₍₂₂₋₂₃₎ bas	0	-0.002	0.009	0.156	1	-0.010	0.005	0.139	2	-0.003	0.007	0.148	0
<i>APOE</i> ₍₂₄₎ bas	0	-0.028	-0.037	0.395	7	0.049	0.057	0.355	5	0.003	0.013	0.377	3
<i>APOE</i> ₍₃₄₋₄₄₎ bas	-0.77	-0.768	-0.764	0.142	100	-0.536	-0.525	0.127	98	-0.621	-0.596	0.135	97
s													
Age*s						0.347	0.346	0.037	100				
Gender*s						0.001	-0.000	0.020	23				
Educ*s						0.021	0.031	0.064	6				
<i>APOE</i> ₍₂₂₋₂₃₎ *s						-0.051	-0.054	0.067	17				
<i>APOE</i> ₍₂₄₎ *s						0.008	0.007	0.077	3				
<i>APOE</i> ₍₃₄₋₄₄₎ *s						-0.011	-0.015	0.239	8				
Δ_1						0.047	0.057	0.083	15				
Δ_2										-1.177	-1.191	0.169	100
Age * Δ_1										-0.487	-0.518	0.120	70
Age * Δ_2										0.065	0.060	0.030	71
Gender * Δ_1										0.036	0.028	0.062	9
Gender * Δ_2										-0.025	-0.019	0.211	7
Educ * Δ_1										-0.010	-0.028	0.287	9
Educ * Δ_2										0.164	0.154	0.210	6
<i>APOE</i> ₍₂₂₋₂₃₎ * Δ_1										0.109	0.102	0.279	3
<i>APOE</i> ₍₂₂₋₂₃₎ * Δ_2										0.029	0.041	0.251	1
<i>APOE</i> ₍₂₄₎ * Δ_1										0.012	-0.008	0.345	63
<i>APOE</i> ₍₂₄₎ * Δ_2										-0.224	-0.379	0.678	6
<i>APOE</i> ₍₃₄₋₄₄₎ * Δ_1										-0.062	-0.134	0.909	4
<i>APOE</i> ₍₃₄₋₄₄₎ * Δ_2										-0.094	-0.071	0.324	3
σ_b^2	0.941	1.112	1.168			0.845	0.848			-0.054	-0.087	0.409	4
σ_ϕ^2	0.504	0.374	0.172			0.273	0.178			0.872	0.920		
										0.591	0.199		