

# Supplement A: Linear Mixed Models for Emotikon Study

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# 1 Background

This supplement accompanies Fühner, T., Granacher, U., Golle, K., & Kliegl, R. (2021). Physical fitness in third-grade primary school: A window on *short-term ontogenesis* with a mixed model analysis of 108,295 children and 515 schools. Scripts and data are available in OSF repository: <https://osf.io/2d8rj/>

Fitting of linear mixed models for model selection, component analyses of the random-effect structures, and control models as well as model comparisons were carried out with the *MixedModels.jl* package in **Julia** (script: FGK21.jl on osf repo); table contents and figures were generated in **R** (script: FGK21.Rmd on osf repo).

## 2 Readme for ‘fgk21.rds’

Number of scores: 525,126

1. Cohort: 9 levels; 2011-2019
2. District: 18 levels
3. BU: 2 levels; distance to Berlin
4. School: 515 levels
5. Child: 108,295 levels; all children are between 8.0 and 8.99 years old at key date (30 September)
6. Sex: “Boys” (n= 53,209), “Girls” (n=55,086)
7. age: test date - middle of month of birthdate
8. Test: 5 levels
  - Endurance (**Run**, cardiorespiratory): 6 minute endurance run [m]; to nearest 9m in 9x18m field
  - Coordination (**Star\_r**): star coordination run [m/s]; 9x9m field, 4 x diagonal = 50.912 m
  - Speed(**S20\_r**): 20-meters sprint [m/s]
  - PowerLOW (SLJ, muscular): standing long jump [cm]
  - PowerUP (BPT, muscular): 1-kg medicine ball push test [m]
9. score - see units
10. zScore

## 3 Preprocessing

- read data
- center age
- compute indicator for quadratic trend of age
- specify contrasts for test factor

```
using RCall, DataFrames, DataFramesMeta, MixedModels, JellyMe4
dat = categorical!(rcopy(R"readRDS($datadir('fgk21.rds'))"));
describe(dat)

dat = @linq dat |>
  transform(
    a1 = :age .- 8.5,
    a2 = (:age .- 8.5) .^2,
  );

contr = merge(
  Dict{nm => SeqDiffCoding() for nm in (:Test, :Sex)},
  Dict{nm => Grouping() for nm in (:School, :Child, :Cohort)},
);
```

## 4 Model formulae

It was apparent that the data would support an LMM with the four test contrasts, linear slope for age, and the sex effect as variance components and correlation parameters for random factors child and school where appropriate. (Age and sex vary between children and cannot be included for this random factor.) Special consideration was given to the structure of the random factor `Cohort` which had only nine levels. We considered four models `m1` to `m4` of increasing complexity as shown in the following. We also estimated each of these model in two alternative parameterizations as described below (i.e., a total of twelve LMMs).

Here are the model formulae:

```

m1  = "~ 1 + FE + (1+Test | Child) + (1+Test+a1+Sex | School) + (1 | Cohort)"
m2  = "~ 1 + FE + (1+Test | Child) + (1+Test+a1+Sex | School) + zerocorr(1+Test | Cohort)"
m3  = "~ 1 + FE + (1+Test | Child) + (1+Test+a1+Sex | School) + (1+Test | Cohort)"
m4  = "~ 1 + FE + (1+Test | Child) + (1+Test+a1+Sex | School) + (1+Test+a1+Sex | Cohort)"

m1L = "~ 1 + FE + (0+Test | Child) + (0+Test+a1+Sex | School) + (1 | Cohort)"
m2L = "~ 1 + FE + (0+Test | Child) + (0+Test+a1+Sex | School) + zerocorr(0+Test | Cohort)"
m3L = "~ 1 + FE + (0+Test | Child) + (0+Test+a1+Sex | School) + (0+Test | Cohort)"
m4L = "~ 1 + FE + (0+Test | Child) + (0+Test+a1+Sex | School) + (0+Test+a1+Sex | Cohort)"

m1LL = "~ 0 + FE + (0+Test | Child) + (0+Test+a1+Sex | School) + (1 | Cohort)"
m2LL = "~ 0 + FE + (0+Test | Child) + (0+Test+a1+Sex | School) + zerocorr(0+Test | Cohort)"
m3LL = "~ 0 + FE + (0+Test | Child) + (0+Test+a1+Sex | School) + (0+Test | Cohort)"
m4LL = "~ 0 + FE + (0+Test | Child) + (0+Test+a1+Sex | School) + (0+Test+a1+Sex | Cohort)"

```

LMM `m1` to `m4` represent the default specification with effects both in the fixed-effect (FE) and the random-effect structure (RES) of the models with increasing numbers corresponding to an increase in complexity of the RES of the random factor `Cohort`. We start with a cohort-related variance component (VC) for the Grand Mean (GM) in LMM `m1`. Then, in LMM `m2` we add cohort-related VCs for the contrast effects specified for the factor `Test` and, in LMM `m3`, also estimate cohort-related correlation parameters (CPs). In the most complex LMM `m4`, we add cohort-related components for the linear effect of age (`a1`) and for the effect for `Sex`.

LMM `m1L` to `m4L` differ from the above only in that in the RES we do not estimate VCs and CPs for contrasts specified for the differences between levels of `Test` (i.e., for test-related effects), but VCs and CPs for the scores (i.e., we exchange 1 for 0). Thus, the CPs should reflect the typical positive manifold of correlations that we expect from a test battery that is intended to measure the latent construct *physical fitness*.

LMM `m1LL` to `m4LL` estimate scores not only in the RES, but also in the FE part of the model. Thus, we estimate the Test scores after statistical adjustment for all the other variables. This is not very informative in the present context because all tests were transformed to z-scores prior to analyses, that is their means were expected to be zero anyway.

LMM `m2` and LMM `m2L` are reported in some detail in the paper. In addition, there are two *post-hoc* control LMMs. The first one tests the significance of adding quadratic trends of age (`m2_agesq`) to `m2`; the second one tests the age x Sex interaction for each of the five tests, that is nested within levels of the `Test` factor (`m2LL_nested`).

## 5 Model selection

- FE: fixed effect part
- RES: random-effect structure)

### 5.1 LMMs with effects in FE and RES

```
show(stdout, MixedModels.likelihoodratioTest(m1, m2, m3, m4))
```

Model Formulae

```
1: zScore ~ 1 + Test + a1 + Sex + Test & a1 + Test & Sex + a1 & Sex + Test & a1 & Sex +
  (1 + Test + a1 + Sex | School) + (1 + Test | Child) +
  (1 | Cohort)
2: zScore ~ 1 + Test + a1 + Sex + Test & a1 + Test & Sex + a1 & Sex + Test & a1 & Sex +
  (1 + Test + a1 + Sex | School) + (1 + Test | Child) +
  MixedModels.ZeroCorr((1 + Test | Cohort))
3: zScore ~ 1 + Test + a1 + Sex + Test & a1 + Test & Sex + a1 & Sex + Test & a1 & Sex +
  (1 + Test + a1 + Sex | School) + (1 + Test | Child) +
  (1 + Test | Cohort)
4: zScore ~ 1 + Test + a1 + Sex + Test & a1 + Test & Sex + a1 & Sex + Test & a1 & Sex +
  (1 + Test + a1 + Sex | School) + (1 + Test | Child) +
  (1 + Test + a1 + Sex | Cohort)
```

| model | dof | deviance     | <sup>2</sup> | <sup>2</sup> -dof | P(> <sup>2</sup> ) | singular? | cum cohort-PC5       |
|-------|-----|--------------|--------------|-------------------|--------------------|-----------|----------------------|
| m1    | 65  | 1276669.7859 |              |                   |                    | false     | na                   |
| m2    | 69  | 1275180.2140 | 1489.5719    | 4                 | <1e-99             | false     | 0.80 (ortho)         |
| m3    | 79  | 1275131.7680 | 48.4460      | 10                | <1e-6              | false     | 0.9986               |
| m4    | 92  | 1275117.6542 | 14.1138      | 13                | 0.3659             | true      | 0.9923, but PC5: 1.0 |

```
mods = [m1, m2, m3, m4];
gof_summary = DataFrame(dof=dof.(mods), deviance=deviance.(mods),
  AIC = aic.(mods), AICc = aicc.(mods), BIC = bic.(mods))
```

| Row | dof | deviance  | AIC       | AICc      | BIC       | Selection    |
|-----|-----|-----------|-----------|-----------|-----------|--------------|
| m1  | 65  | 1.27667e6 | 1.27680e6 | 1.27680e6 | 1.27753e6 | -            |
| m2  | 69  | 1.27518e6 | 1.27532e6 | 1.27532e6 | 1.27609e6 | +, using BIC |
| m3  | 79  | 1.27513e6 | 1.27529e6 | 1.27529e6 | 1.27617e6 | -            |
| m4  | 92  | 1.27512e6 | 1.27530e6 | 1.27530e6 | 1.27633e6 | -            |

The comparisons of goodness of fit suggested that m2 and m3 were supported by the data. BIC suggested to go with m2 and since we did not have any specific hypotheses relating to cohort-related correlation parameters. Therefore, m2 selected LMM m2. Goodness-of-fit statistics for reparameterized alternatives also were in line with this selection.

## 6 LMM with CPs for test effects/contrasts (Table 1 and Table 3)

### 6.1 LMM m2

```
f2 = @formula zScore ~ 1 + Test*a1*Sex +
      (1+Test+a1+Sex | School) + (1+Test | Child) + zerocorr(1+Test | Cohort);

m2 = fit(MixedModel, f2, dat, contrasts=contr);
show(stdout, m2)
```

Linear mixed model fit by maximum likelihood

```
zScore ~ 1 + Test + a1 + Sex + Test & a1 + Test & Sex + a1 & Sex + Test & a1 & Sex +
      (1 + Test + a1 + Sex | School) + (1 + Test | Child) +
      MixedModels.ZeroCorr((1 + Test | Cohort))
```

| logLik       | -2 logLik    | AIC          | AICc         | BIC          |
|--------------|--------------|--------------|--------------|--------------|
| -637590.1070 | 1275180.2140 | 1275318.2140 | 1275318.2324 | 1276089.0402 |

Variance components:

|          | Column       | Variance  | Std.Dev.  | Corr.                               |
|----------|--------------|-----------|-----------|-------------------------------------|
| Child    | (Intercept)  | 0.3329066 | 0.5769806 |                                     |
|          | Test: Star_r | 0.3949430 | 0.6284449 | +0.13                               |
|          | Test: S20_r  | 0.3108601 | 0.5575483 | +0.07 -0.51                         |
|          | Test: SLJ    | 0.2255198 | 0.4748893 | +0.08 +0.02 -0.35                   |
|          | Test: BPT    | 0.5154925 | 0.7179781 | -0.31 +0.14 -0.20 -0.27             |
| School   | (Intercept)  | 0.0379211 | 0.1947335 |                                     |
|          | Test: Star_r | 0.1428635 | 0.3779729 | +0.15                               |
|          | Test: S20_r  | 0.1470948 | 0.3835294 | -0.13 -0.59                         |
|          | Test: SLJ    | 0.0861069 | 0.2934398 | -0.11 +0.02 -0.50                   |
|          | Test: BPT    | 0.0862926 | 0.2937560 | -0.19 -0.05 +0.06 -0.39             |
|          | a1           | 0.0086981 | 0.0932633 | +0.48 -0.03 -0.10 -0.01 -0.10       |
| Cohort   | Sex: male    | 0.0022442 | 0.0473728 | +0.09 -0.14 +0.13 +0.05 -0.19 +0.26 |
|          | (Intercept)  | 0.0002206 | 0.0148527 |                                     |
|          | Test: Star_r | 0.0020748 | 0.0455502 | .                                   |
|          | Test: S20_r  | 0.0061490 | 0.0784158 | .                                   |
|          | Test: SLJ    | 0.0073707 | 0.0858530 | .                                   |
| Residual | Test: BPT    | 0.0015895 | 0.0398688 | .                                   |
|          |              | 0.2946762 | 0.5428408 |                                     |

Number of obs: 525126; levels of grouping factors: 108295, 515, 9

Fixed-effects parameters:

|                   | Coef.       | Std. Error | z     | Pr(> z ) |
|-------------------|-------------|------------|-------|----------|
| (Intercept)       | -0.0412415  | 0.0103181  | -4.00 | <1e-4    |
| Test: Star_r      | 0.0091823   | 0.0230736  | 0.40  | 0.6907   |
| Test: S20_r       | -0.0317626  | 0.0314911  | -1.01 | 0.3132   |
| Test: SLJ         | 0.0401004   | 0.0316932  | 1.27  | 0.2058   |
| Test: BPT         | -0.00658233 | 0.0191624  | -0.34 | 0.7312   |
| a1                | 0.262406    | 0.00826918 | 31.73 | <1e-99   |
| Sex: male         | 0.398323    | 0.00460118 | 86.57 | <1e-99   |
| Test: Star_r & a1 | 0.207036    | 0.0111089  | 18.64 | <1e-76   |
| Test: S20_r & a1  | -0.0638853  | 0.0106115  | -6.02 | <1e-8    |
| Test: SLJ & a1    | -0.00242996 | 0.0100449  | -0.24 | 0.8089   |

|                               |            |            |        |        |
|-------------------------------|------------|------------|--------|--------|
| Test: BPT & a1                | 0.298104   | 0.0116072  | 25.68  | <1e-99 |
| Test: Star_r & Sex: male      | -0.242993  | 0.00633029 | -38.39 | <1e-99 |
| Test: S20_r & Sex: male       | 0.0767793  | 0.00604287 | 12.71  | <1e-36 |
| Test: SLJ & Sex: male         | 0.070909   | 0.0057178  | 12.40  | <1e-34 |
| Test: BPT & Sex: male         | 0.287073   | 0.00661763 | 43.38  | <1e-99 |
| a1 & Sex: male                | 0.00189488 | 0.0133182  | 0.14   | 0.8869 |
| Test: Star_r & a1 & Sex: male | 0.0372992  | 0.0214434  | 1.74   | 0.0820 |
| Test: S20_r & a1 & Sex: male  | -0.0128506 | 0.0204696  | -0.63  | 0.5301 |
| Test: SLJ & a1 & Sex: male    | -0.019174  | 0.0193766  | -0.99  | 0.3224 |
| Test: BPT & a1 & Sex: male    | 0.0241119  | 0.0224232  | 1.08   | 0.2822 |

## 6.2 Effects PCA w/ CPs

### 6.2.1 Random factor Child

```
m2_pca=MixedModels.PCA(m2, corr=true)
show(stdout, m2_pca.Child, stddevs=true)
```

```
Child =
Principal components based on correlation matrix
(Intercept)  1.0    .    .    .    .
Test: Star_r  0.13   1.0    .    .    .
Test: S20_r   0.07  -0.51   1.0    .    .
Test: SLJ     0.08   0.02  -0.35   1.0    .
Test: BPT    -0.31   0.14  -0.2   -0.27   1.0
```

```
Normalized cumulative variances:
[0.3307, 0.6218, 0.824, 0.9345, 1.0]
```

```
Component loadings
          PC1    PC2    PC3    PC4    PC5
(Intercept) -0.04   0.54   0.64   0.53  -0.12
Test: Star_r  0.6    0.01   0.47  -0.42   0.49
Test: S20_r  -0.7   -0.04   0.15  -0.04   0.69
Test: SLJ     0.29   0.52  -0.59   0.3    0.46
Test: BPT     0.24  -0.66   0.05   0.67   0.24
```

### 6.2.2 Random factor School

```
show(stdout, m2_pca.School, stddevs=true)
```

```
School =
Principal components based on correlation matrix
(Intercept)  1.0    .    .    .    .    .    .
Test: Star_r  0.15   1.0    .    .    .    .    .
Test: S20_r  -0.13  -0.59   1.0    .    .    .    .
Test: SLJ    -0.11   0.02  -0.5    1.0    .    .    .
Test: BPT    -0.19  -0.05   0.06  -0.39   1.0    .    .
a1           0.48  -0.03  -0.1   -0.01  -0.1    1.0    .
Sex: male    0.09  -0.14   0.13   0.05  -0.19   0.26   1.0
```

```
Normalized cumulative variances:
[0.2768, 0.5103, 0.6989, 0.8107, 0.9155, 0.975, 1.0]
```

## Component loadings

|              | PC1   | PC2   | PC3   | PC4   | PC5   | PC6   | PC7   |
|--------------|-------|-------|-------|-------|-------|-------|-------|
| (Intercept)  | -0.3  | 0.46  | 0.4   | -0.36 | 0.01  | -0.63 | -0.1  |
| Test: Star_r | -0.44 | -0.29 | 0.39  | 0.11  | -0.54 | 0.25  | -0.45 |
| Test: S20_r  | 0.59  | 0.29  | -0.11 | -0.26 | -0.17 | 0.12  | -0.66 |
| Test: SLJ    | -0.43 | -0.16 | -0.56 | 0.06  | 0.39  | -0.21 | -0.53 |
| Test: BPT    | 0.34  | -0.23 | 0.47  | 0.56  | 0.38  | -0.3  | -0.25 |
| a1           | -0.25 | 0.55  | 0.22  | 0.16  | 0.44  | 0.59  | -0.09 |
| Sex: male    | -0.04 | 0.48  | -0.29 | 0.67  | -0.43 | -0.21 | 0.04  |

## 7 LMM with CPs for Test scores (Table 2)

### 7.1 LMM m2L

- The levels LMM m2L estimates CPs between test scores.
- This is a reparameterized version of the reference LMM m2.

```
f2L = @formula zScore ~ 1 + Test*a1*Sex +
      (0+Test+a1+Sex | School) + (0+Test | Child) + zerocorr(0+Test | Cohort);

m2L = fit(MixedModel, f2L, dat, contrasts=contr);
show(stdout, m2L)
```

Linear mixed model fit by maximum likelihood

```
zScore ~ 1 + Test + a1 + Sex + Test & a1 + Test & Sex + a1 & Sex + Test & a1 & Sex +
      (0 + Test + a1 + Sex | School) + (0 + Test | Child) +
      MixedModels.ZeroCorr((0 + Test | Cohort))
```

| logLik       | -2 logLik    | AIC          | AICc         | BIC          |
|--------------|--------------|--------------|--------------|--------------|
| -637584.2256 | 1275168.4513 | 1275306.4513 | 1275306.4697 | 1276077.2774 |

### Variance components:

|          | Column       | Variance  | Std.Dev.  | Corr.                               |
|----------|--------------|-----------|-----------|-------------------------------------|
| Child    | Test: Run    | 0.4720053 | 0.6870265 |                                     |
|          | Test: Star_r | 0.5149263 | 0.7175837 | +0.57                               |
|          | Test: S20_r  | 0.5333160 | 0.7302849 | +0.63 +0.67                         |
|          | Test: SLJ    | 0.5887047 | 0.7672709 | +0.60 +0.66 +0.77                   |
|          | Test: BPT    | 0.4920322 | 0.7014501 | +0.25 +0.45 +0.43 +0.50             |
| School   | Test: Run    | 0.0905314 | 0.3008843 |                                     |
|          | Test: Star_r | 0.1297187 | 0.3601648 | +0.36                               |
|          | Test: S20_r  | 0.0888125 | 0.2980142 | +0.34 +0.33                         |
|          | Test: SLJ    | 0.0628468 | 0.2506927 | +0.37 +0.39 +0.43                   |
|          | Test: BPT    | 0.0552228 | 0.2349952 | +0.19 +0.19 +0.28 +0.27             |
| Sex      | a1           | 0.0084566 | 0.0919599 | +0.45 +0.34 +0.29 +0.32 +0.23       |
|          | Sex: male    | 0.0022439 | 0.0473694 | +0.12 -0.05 +0.11 +0.19 -0.03 +0.26 |
|          |              |           |           |                                     |
| Cohort   | Test: Run    | 0.0027367 | 0.0523136 |                                     |
|          | Test: Star_r | 0.0012155 | 0.0348643 | .                                   |
|          | Test: S20_r  | 0.0033599 | 0.0579650 | . .                                 |
|          | Test: SLJ    | 0.0012840 | 0.0358327 | . . .                               |
|          | Test: BPT    | 0.0006433 | 0.0253630 | . . . .                             |
| Residual |              | 0.2798248 | 0.5289847 |                                     |

Number of obs: 525126; levels of grouping factors: 108295, 515, 9

### Fixed-effects parameters:

|                               | Coef.       | Std. Error | z      | Pr(> z ) |
|-------------------------------|-------------|------------|--------|----------|
| (Intercept)                   | -0.0413414  | 0.0111307  | -3.71  | 0.0002   |
| Test: Star_r                  | 0.00914238  | 0.0272306  | 0.34   | 0.7371   |
| Test: S20_r                   | -0.0317054  | 0.0286019  | -1.11  | 0.2676   |
| Test: SLJ                     | 0.0402146   | 0.0265087  | 1.52   | 0.1293   |
| Test: BPT                     | -0.00677574 | 0.0201379  | -0.34  | 0.7365   |
| a1                            | 0.262707    | 0.00823925 | 31.88  | <1e-99   |
| Sex: male                     | 0.398338    | 0.00460132 | 86.57  | <1e-99   |
| Test: Star_r & a1             | 0.20653     | 0.0111167  | 18.58  | <1e-76   |
| Test: S20_r & a1              | -0.063456   | 0.0106144  | -5.98  | <1e-8    |
| Test: SLJ & a1                | -0.0019081  | 0.0100451  | -0.19  | 0.8493   |
| Test: BPT & a1                | 0.297183    | 0.0116108  | 25.60  | <1e-99   |
| Test: Star_r & Sex: male      | -0.242973   | 0.00633076 | -38.38 | <1e-99   |
| Test: S20_r & Sex: male       | 0.0767645   | 0.00604373 | 12.70  | <1e-36   |
| Test: SLJ & Sex: male         | 0.070886    | 0.00571752 | 12.40  | <1e-34   |
| Test: BPT & Sex: male         | 0.287099    | 0.00661733 | 43.39  | <1e-99   |
| a1 & Sex: male                | 0.00189748  | 0.0133187  | 0.14   | 0.8867   |
| Test: Star_r & a1 & Sex: male | 0.0372593   | 0.0214449  | 1.74   | 0.0823   |
| Test: S20_r & a1 & Sex: male  | -0.01281    | 0.0204726  | -0.63  | 0.5315   |
| Test: SLJ & a1 & Sex: male    | -0.0191215  | 0.0193756  | -0.99  | 0.3237   |
| Test: BPT & a1 & Sex: male    | 0.0240643   | 0.0224222  | 1.07   | 0.2832   |

## 7.2 Scores PCA w/ CPs

### 7.2.1 Random factor Child

```
m2L_pca=MixedModels.PCA(m2L, corr=true)
show(stdout, m2L_pca.Child, stddevs=true)
```

```
Child =
Principal components based on correlation matrix
Test: Run      1.0      .      .      .      .
Test: Star_r   0.57    1.0      .      .      .
Test: S20_r    0.63    0.67    1.0      .      .
Test: SLJ      0.6     0.66    0.77    1.0      .
Test: BPT      0.25    0.45    0.43    0.5     1.0
```

```
Normalized cumulative variances:
[0.6513, 0.8056, 0.8822, 0.9559, 1.0]
```

```
Component loadings
          PC1      PC2      PC3      PC4      PC5
Test: Run   -0.42    0.51    0.72    0.19   -0.01
Test: Star_r -0.47    0.02   -0.48    0.73   -0.09
Test: S20_r  -0.49    0.13   -0.27   -0.41    0.71
Test: SLJ    -0.49    0.0    -0.16   -0.5    -0.69
Test: BPT    -0.34   -0.85    0.38    0.07    0.1
```

### 7.2.2 Random factor School

```
show(stdout, m2L_pca.School, stddevs=true)
```

```
School =
```

```
Principal components based on correlation matrix
```

|              |      |       |      |      |       |      |     |
|--------------|------|-------|------|------|-------|------|-----|
| Test: Run    | 1.0  | .     | .    | .    | .     | .    | .   |
| Test: Star_r | 0.36 | 1.0   | .    | .    | .     | .    | .   |
| Test: S20_r  | 0.34 | 0.33  | 1.0  | .    | .     | .    | .   |
| Test: SLJ    | 0.37 | 0.39  | 0.43 | 1.0  | .     | .    | .   |
| Test: BPT    | 0.19 | 0.19  | 0.28 | 0.27 | 1.0   | .    | .   |
| a1           | 0.45 | 0.34  | 0.29 | 0.32 | 0.23  | 1.0  | .   |
| Sex: male    | 0.12 | -0.05 | 0.11 | 0.19 | -0.03 | 0.26 | 1.0 |

```
Normalized cumulative variances:
```

```
[0.3805, 0.539, 0.6615, 0.7688, 0.8563, 0.9349, 1.0]
```

```
Component loadings
```

|              | PC1   | PC2   | PC3   | PC4   | PC5   | PC6   | PC7   |
|--------------|-------|-------|-------|-------|-------|-------|-------|
| Test: Run    | -0.43 | 0.05  | -0.32 | 0.28  | -0.57 | 0.45  | -0.32 |
| Test: Star_r | -0.4  | -0.31 | -0.45 | -0.11 | 0.54  | -0.22 | -0.43 |
| Test: S20_r  | -0.42 | -0.1  | 0.22  | -0.49 | -0.49 | -0.54 | 0.01  |
| Test: SLJ    | -0.45 | 0.01  | 0.09  | -0.46 | 0.25  | 0.57  | 0.44  |
| Test: BPT    | -0.29 | -0.36 | 0.74  | 0.41  | 0.15  | 0.08  | -0.21 |
| a1           | -0.42 | 0.26  | -0.16 | 0.53  | 0.11  | -0.35 | 0.55  |
| Sex: male    | -0.16 | 0.83  | 0.25  | -0.1  | 0.21  | -0.04 | -0.4  |

## 8 LMM with quadratic trends of age

Adding a quadratic trend for age to the reference LMM m2 did not significantly increase the goodness of fit.

```
f2_agesq = @formula zScore ~ 1 + Test*(a1+a2)*Sex +
  (1+Test+a1+Sex | School) + (1+Test | Child) + zerocorr(1+Test | Cohort);
```

```
m2_agesq = fit(MixedModel, f2_agesq, dat, contrasts=contr);
show(stdout, m2_agesq);
```

```
show(stdout, MixedModels.likelihoodratioTest(m2, m2_agesq))
```

```
Model Formulae
```

```
1: zScore ~ 1 + Test + a1 + Sex +
  Test & a1 + Test & Sex + a1 & Sex +
  Test & a1 & Sex +
  (1 + Test + a1 + Sex | School) + (1 + Test | Child) +
  MixedModels.ZeroCorr((1 + Test | Cohort))
2: zScore ~ 1 + Test + a1 + a2 + Sex +
  Test & a1 + Test & a2 + Test & Sex + a1 & Sex + a2 & Sex +
  Test & a1 & Sex + Test & a2 & Sex +
  (1 + Test + a1 + Sex | School) + (1 + Test | Child) +
  MixedModels.ZeroCorr((1 + Test | Cohort))
```

|     | model-dof | deviance     | $\chi^2$ | $\chi^2$ -dof | P(> $\chi^2$ ) |
|-----|-----------|--------------|----------|---------------|----------------|
| [1] | 69        | 1275180.2140 |          |               |                |
| [2] | 79        | 1275171.0417 | 9.1723   | 10            | 0.5158         |

## 9 LMM with Age x Sex interactions nested in levels of Test

- The nested LMM m2LL estimates the age x sex interaction for each (level of) test.
- This is a reparameterized version of the reference LMM m2.

The following details about this LMM are not reported in the paper, only here.

```
f2LL_nested = @formula zScore ~ 0 + Test & (a1*Sex) +
              (0+Test+a1+Sex | School) + (0+Test | Child) + zerocorr(0+Test | Cohort);

m2LL_nested = fit(MixedModel, f2LL_nested, dat, contrasts=contr);
show(stdout, m2LL_nested)
```

Linear mixed model fit by maximum likelihood

```
zScore ~ 0 + Test & a1 + Test & Sex + Test & a1 & Sex +
        (0 + Test + a1 + Sex | School) + (0 + Test | Child) +
        MixedModels.ZeroCorr((0 + Test | Cohort))
```

| logLik       | -2 logLik    | AIC          | AICc         | BIC          |
|--------------|--------------|--------------|--------------|--------------|
| -637584.1432 | 1275168.2864 | 1275306.2864 | 1275306.3048 | 1276077.1125 |

Variance components:

|          | Column       | Variance  | Std.Dev.  | Corr.                               |
|----------|--------------|-----------|-----------|-------------------------------------|
| Child    | Test: Run    | 0.4723237 | 0.6872581 |                                     |
|          | Test: Star_r | 0.5150818 | 0.7176920 | +0.57                               |
|          | Test: S20_r  | 0.5336122 | 0.7304876 | +0.63 +0.67                         |
|          | Test: SLJ    | 0.5889387 | 0.7674234 | +0.60 +0.66 +0.77                   |
|          | Test: BPT    | 0.4922653 | 0.7016162 | +0.25 +0.45 +0.43 +0.50             |
| School   | Test: Run    | 0.0895243 | 0.2992060 |                                     |
|          | Test: Star_r | 0.1288480 | 0.3589540 | +0.35                               |
|          | Test: S20_r  | 0.0883273 | 0.2971992 | +0.34 +0.33                         |
|          | Test: SLJ    | 0.0621314 | 0.2492617 | +0.37 +0.39 +0.43                   |
|          | Test: BPT    | 0.0549164 | 0.2343425 | +0.19 +0.19 +0.28 +0.26             |
|          | a1           | 0.0086935 | 0.0932387 | +0.45 +0.34 +0.28 +0.32 +0.22       |
| Cohort   | Sex: male    | 0.0022428 | 0.0473580 | +0.12 -0.05 +0.11 +0.19 -0.03 +0.26 |
|          | Test: Run    | 0.0025935 | 0.0509261 |                                     |
|          | Test: Star_r | 0.0012459 | 0.0352978 | .                                   |
|          | Test: S20_r  | 0.0034555 | 0.0587831 | .                                   |
|          | Test: SLJ    | 0.0012469 | 0.0353118 | .                                   |
| Residual | Test: BPT    | 0.0006483 | 0.0254609 | .                                   |
|          |              | 0.2795697 | 0.5287435 |                                     |

Number of obs: 525126; levels of grouping factors: 108295, 515, 9

Fixed-effects parameters:

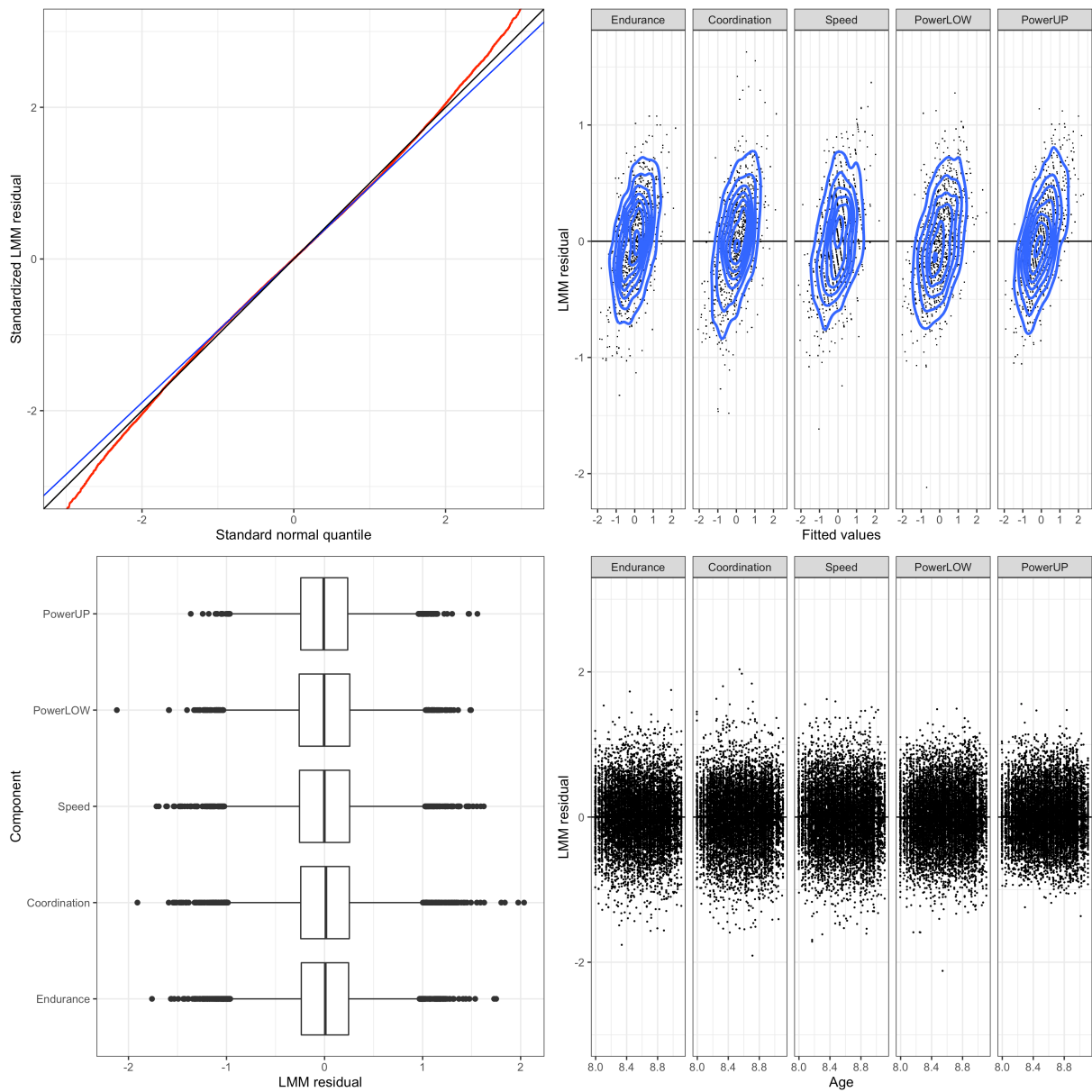
|                         | Coef.     | Std. Error | z      | Pr(> z ) |
|-------------------------|-----------|------------|--------|----------|
| Test: Run & a1          | 0.0767566 | 0.0106853  | 7.18   | <1e-12   |
| Test: Star_r & a1       | 0.283328  | 0.0109127  | 25.96  | <1e-99   |
| Test: S20_r & a1        | 0.219841  | 0.0109809  | 20.02  | <1e-88   |
| Test: SLJ & a1          | 0.217916  | 0.0112423  | 19.38  | <1e-82   |
| Test: BPT & a1          | 0.515148  | 0.0107103  | 48.10  | <1e-99   |
| Test: Run & Sex: female | -0.274688 | 0.0220087  | -12.48 | <1e-35   |

|                               |            |           |        |        |
|-------------------------------|------------|-----------|--------|--------|
| Test: Star_r & Sex: female    | -0.144083  | 0.020475  | -7.04  | <1e-11 |
| Test: S20_r & Sex: female     | -0.214177  | 0.0240693 | -8.90  | <1e-18 |
| Test: SLJ & Sex: female       | -0.209461  | 0.016783  | -12.48 | <1e-35 |
| Test: BPT & Sex: female       | -0.359744  | 0.0142742 | -25.20 | <1e-99 |
| Test: Run & Sex: male         | 0.186184   | 0.0221835 | 8.39   | <1e-16 |
| Test: Star_r & Sex: male      | 0.0738122  | 0.0204101 | 3.62   | 0.0003 |
| Test: S20_r & Sex: male       | 0.0804841  | 0.0242201 | 3.32   | 0.0009 |
| Test: SLJ & Sex: male         | 0.156088   | 0.017084  | 9.14   | <1e-19 |
| Test: BPT & Sex: male         | 0.2929     | 0.0142442 | 20.56  | <1e-93 |
| Test: Run & a1 & Sex: male    | -0.0173922 | 0.0186248 | -0.93  | 0.3504 |
| Test: Star_r & a1 & Sex: male | 0.0198723  | 0.0191305 | 1.04   | 0.2989 |
| Test: S20_r & a1 & Sex: male  | 0.00706046 | 0.0192615 | 0.37   | 0.7139 |
| Test: SLJ & a1 & Sex: male    | -0.012061  | 0.0198405 | -0.61  | 0.5433 |
| Test: BPT & a1 & Sex: male    | 0.0120077  | 0.0187164 | 0.64   | 0.5212 |

None of the five interaction terms (last five lines in table above) is significant.

## 10 A few standard observation-level residual plots

The figure is based on a random sample of 50,000 residuals (i.e.,  $\sim 10\%$ ); it takes too long otherwise. Repeated execution did not reveal any disturbing patterns.



## 11 Julia and package versions

```
using Pkg
show(stdout, Pkg.status())
using InteractiveUtils
show(stdout, versioninfo(verbose=true))
```

```
Status `~/Google Drive/git_projects/SMLP2020/Project.toml`
[a93c6f00] DataFrames v0.22.5
[1313f7d8] DataFramesMeta v0.6.0
[ff71e718] MixedModels v3.4.0
[6f49c342] RCall v0.13.10
```

```
Julia Version 1.5.3
Commit 788b2c77c1 (2020-11-09 13:37 UTC)
Platform Info: OS: macOS (x86_64-apple-darwin18.7.0)
```

## 12 References

- Bates, D., Alday, P., Kleinschmidt, D., et al. (2021, March 8). JuliaStats/MixedModels.jl: v3.4.0 (Version v3.4.0). Zenodo. <http://doi.org/10.5281/zenodo.4589101>.
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- Bates, D., Maechler, M., Bolker, B., Walker, S. (2015). Fitting Linear Mixed-Effects Models Using lme4. *Journal of Statistical Software*, 67, 1-48. doi:10.18637/jss.v067.i01. (Version 1.1.26)
- Bolker, B., & Robinson, R. (2020). broom.mixed: Tidying Methods for Mixed Models. R package version 0.2.6. <https://CRAN.R-project.org/package=broom.mixed>
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- Wickham et al., (2019). Welcome to the tidyverse. *Journal of Open Source Software*, 4(43), 1686, <https://doi.org/10.21105/joss.01686> (Version 1.3.0)
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# Supplement B: Reanalyses of Golle et al. (2015)

2021-02-16 (updated: 2021-03-24 10:34:28)

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## 1 Background

### 1.1 Reference

This script is for a Supplement that accompanies Fühner, T., Granacher, U., Golle, K., & Kliegl, R. (2021). Physical fitness in third-grade of primary school: A mixed model analysis of 108,295 children and 515 schools. Scripts and data are available in OSF repository: <https://osf.io/2d8rj/>

### 1.2 Overview

- Figure 1 of paper (only in script)
- Reanalysis of longitudinal profiles
- Analysis of cross-sectional age effect and age x sex interactions
  - aggregating across tests within the four years of assessment
  - separately for each test within each of the four years of assessment

## 2 Longitudinal and cross-sectional ontogenesis (2006 to 2009)

We reanalyzed the longitudinal data from the first EMOTIKON project reported in Golle et al. (2015). Physical Fitness Percentiles of German Children Aged 9–12 Years: Findings from a Longitudinal Study. *PLoS ONE*, 10, 11 (doi:10.1371/journal.pone.0142393). The primary purpose was to use these data for Figure 1 in the paper.

We test age, sex, and age x sex effects for the longitudinal data (i.e., across four assessments). This is basically a reanalysis of the paper with LMMs.

The longitudinal sample comprised 152 boys and 88 girls. Therefore, we examined age x sex interactions for five fitness components, corresponding to the ones used in the paper **within** the four years of assessment, that is look at the data also from this cross-sectional perspective. Note that the specific tests used in this first Emotikon study were replaced with different tests for the same components of physical fitness in the current one.

In the **longitudinal LMM**, there was significant growth for each test (decelerating for **Endurance** and **Coordination**) Boys outperformed girls; this sex effect was not significant for **Coordination**. The interaction between age and sex was significant only for **PowerUP** (i.e, BPT) with larger growth for boys than girls.

With four **cross-sectional LMMs** (i.e., within each year of assessment), we also tested the between-subject age differences. There were no age effects or age x sex interactions – neither when aggregating across the five tests nor within any of the five tests. And this was true for all four years of assesement.

### 3 Setup

Variables for this re-analysis were extracted from a comprehensive data file; tests were z-transformed with mean and standard deviation of first assessment in 2006.

The following variables are used.

1. School: 27 levels
2. Child: 240 levels; all children were tested four times (2006 - 2009)
3. Sex: “Boys” (n=152), “Girls” (n=88)
4. age: test date - middle of month of birthdate
5. year: 2006 - 2009
6. Test: 5 levels:
  - Endurance (**Run**; cardiorespiratory): 6 minute endurance run [m]; to nearest 9m in 9x18m field
  - Coordination (**Star\_r**): Star coordination run [m/s]; 9x9m field, 4 x diagonal = 50.912 m
  - Speed(**S50\_r**): 50-meters sprint [m/s]
  - PowerLOW (THJ; muscular): tripe hop jump [cm]
  - PowerUP (BPT; muscular): (1-kg medicine) ball push test [m] with one arm
7. zScore

### 4 Figure 1

This code chunk generates Figure 1 in the paper.

## 5 Longitudinal LMM: age (2nd-order) x Sex within Test

### 5.1 LMM

#### 5.1.1 Parsimonious LMM selection

Parsiomonious LMM section followed the general recommendations of Bates et al. (2015). Details are available in script on osf repo.

#### 5.1.2 Parsimoious longitudinal LMM for 9.00 to 12.99 year old

```
lmm_long_simple <- lmer(zScore ~ 1 + Test/(Sex*a1 + a2) +
                        (1 + a1 | Child) + (1 + a1 + a2 || School),
```

```

                                data=dat, REML=FALSE, control=lmerControl(calc.derivs=FALSE))
print(summary(lmm_long_simple), cor=FALSE)

```

```

## Linear mixed model fit by maximum likelihood ['lmerMod']
## Formula: zScore ~ 1 + Test/(Sex * a1 + a2) + (1 + a1 | Child) + ((1 |
##      School) + (0 + a1 | School) + (0 + a2 | School))
##      Data: dat
## Control: lmerControl(calc.derivs = FALSE)
##
##      AIC      BIC   logLik deviance df.resid
## 11376.7 11583.9 -5656.3 11312.7      4768
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -4.4644 -0.6102 -0.0037  0.5852  4.9275
##
## Random effects:
##      Groups      Name      Variance Std.Dev. Corr
##      Child      (Intercept) 0.518560 0.72011
##              a1          0.008501 0.09220  0.56
##      School      (Intercept) 0.030732 0.17531
##      School.1 a1          0.004415 0.06645
##      School.2 a2          0.004464 0.06681
##      Residual              0.517498 0.71937
## Number of obs: 4800, groups:  Child, 240; School, 27
##
## Fixed effects:
##
##              Estimate Std. Error t value
## (Intercept)      0.884625   0.062139 14.236
## Test2-1          0.590932   0.051044 11.577
## Test3-2         -0.358435   0.051044 -7.022
## Test4-3          0.272625   0.051044  5.341
## Test5-4          0.167039   0.051044  3.272
## TestEndurance:Sex2-1 0.636114   0.109353  5.817
## TestCoordination:Sex2-1 0.269003   0.109353  2.460
## TestSpeed:Sex2-1    0.232640   0.109353  2.127
## TestPowerLOW:Sex2-1 0.277652   0.109353  2.539
## TestPowerUP:Sex2-1  1.018715   0.109353  9.316
## TestEndurance:a1    0.201382   0.026252  7.671
## TestCoordination:a1 0.549028   0.026252 20.914
## TestSpeed:a1        0.434773   0.026252 16.561
## TestPowerLOW:a1     0.569085   0.026252 21.678
## TestPowerUP:a1      0.778939   0.026252 29.671
## TestEndurance:a2    -0.087447   0.024584 -3.557
## TestCoordination:a2 -0.080338   0.024584 -3.268
## TestSpeed:a2        -0.027774   0.024584 -1.130
## TestPowerLOW:a2     -0.040876   0.024584 -1.663
## TestPowerUP:a2      -0.018337   0.024584 -0.746
## TestEndurance:Sex2-1:a1 -0.060012   0.044328 -1.354
## TestCoordination:Sex2-1:a1 -0.003030   0.044328 -0.068
## TestSpeed:Sex2-1:a1  -0.064772   0.044328 -1.461
## TestPowerLOW:Sex2-1:a1 -0.003465   0.044328 -0.078
## TestPowerUP:Sex2-1:a1  0.099951   0.044328  2.255

```

## 5.2 Summary

- Note
  - “linear growth” refers to significant linear trend of age
  - “decelerating growth” refers to significant negative quadratic trend of age.
- Age and Sex: Boys > girls and significant linear growth across age for all tests. In addition, decelerating growth for Endurance and Coordination, and a significantly larger linear growth for boys than girls for PowerUP
- Test contrasts
  - Coordination grows more than Endurance and more than Speed
  - PowerLOW grows more than Speed, but less than PowerUP
- Variance components and correlation parameters
  - Child: There are reliable individual differences between children’s GM and their linear rate of growth and they correlate positively (.56; i.e., Matthew effect.)
  - School: There are reliable differences between schools’s GM and between their second-order growth-rates; no support for correlation parameters.

## 6 Cross-sectional LMMs

### 6.1 LMM for 9 to 10 year old children (insets of Figure 1)

#### 6.1.1 Parsimonious LMM selection

Parsimonious LMM section followed the general recommendations of Bates et al. (2015). Details are available in script on osf repo.

```
contrasts(dat06$Sex) <- (-1)*MASS::contr.sdif(2)
dat06$sex <- ifelse(dat06$Sex == "Boys", +1/2, -1/2)
contrasts(dat06$Test) <- MASS::contr.sdif(5)
dat06$a1 <- dat06$age - 9.5 # center
dat06$a2 <- dat06$a1^2

lmm_cross06 <- lmer(zScore ~ 1 + Test/((a1+a2)*Sex) + (1 | Child) + (1 | School),
                    data=dat06, REML=FALSE, control=lmerControl(calc.derivs=FALSE))
summary(rePCA(lmm_cross06))
print(summary(lmm_cross06))

# ... further simplification: only main effects of age and sex within Test as fixed effects
lmm_cross_simple06 <- lmer(zScore ~ 1 + Test/(a1+Sex) + (1 | Child) + (1 | School),
                           data=dat06, REML=FALSE, control=lmerControl(calc.derivs=FALSE))

anova(lmm_cross_simple06, lmm_cross06)

print(summary(lmm_cross_simple06), cor=FALSE)
```

#### 6.1.2 Parsimonious crosssectional LMMs

We test the age effect and age x sex interaction nested within each of the four assessments. Note insets in Figure 1 show only data from first assessment.

```

dat$Year <- factor(dat$year)

lmm_cross_simple1 <- lmer(zScore ~ 1 + Year/(Test*a1*Sex) + (1 | Child) + (1 | School),
                          data=dat, REML=FALSE, control=lmerControl(calc.derivs=FALSE))

# without age effect
lmm_cross_noage1 <- lmer(zScore ~ 1 + Year/(Test*Sex) + (1 | Child) + (1 | School),
                          data=dat, REML=FALSE, control=lmerControl(calc.derivs=FALSE))

anova(lmm_cross_noage1, lmm_cross_simple1)

```

#### 6.1.2.1 Age and sex nested within years

```

## Data: dat
## Models:
## lmm_cross_noage1: zScore ~ 1 + Year/(Test * Sex) + (1 | Child) + (1 | School)
## lmm_cross_simple1: zScore ~ 1 + Year/(Test * a1 * Sex) + (1 | Child) + (1 | School)
##
##          npar    AIC    BIC logLik deviance  Chisq Df Pr(>Chisq)
## lmm_cross_noage1    43 11480 11758 -5696.9    11394
## lmm_cross_simple1   83 11510 12048 -5672.2    11344 49.382 40      0.1469

```

##### Summary

Removing age from the LMM does not significantly reduce the goodness of fit. There is no evidence for significant age effect and also no evidence for significant age x sex interactions when aggregating across the five tests within any of the four assessments.

```

lmm_cross_simple2 <- lmer(zScore ~ 1 + Year/Test/(a1*Sex) + (1 | Child) + (1 | School),
                          data=dat, REML=FALSE, control=lmerControl(calc.derivs=FALSE))

# without age effect
lmm_cross_noage2 <- lmer(zScore ~ 1 + Year/Test/Sex + (1 | Child) + (1 | School),
                          data=dat, REML=FALSE, control=lmerControl(calc.derivs=FALSE))

anova(lmm_cross_noage2, lmm_cross_simple2)

```

#### 6.1.2.2 Age and sex nested within tests nested within years

```

## Data: dat
## Models:
## lmm_cross_noage2: zScore ~ 1 + Year/Test/Sex + (1 | Child) + (1 | School)
## lmm_cross_simple2: zScore ~ 1 + Year/Test/(a1 * Sex) + (1 | Child) + (1 | School)
##
##          npar    AIC    BIC logLik deviance  Chisq Df Pr(>Chisq)
## lmm_cross_noage2    43 11480 11758 -5696.9    11394
## lmm_cross_simple2   83 11510 12048 -5672.2    11344 49.382 40      0.1469

```

##### Summary

Removing age from the LMM does not significantly reduce the goodness of fit. Thus, There is no evidence for significant age effects and also no evidence for significant age x sex interactions when tested separately for each of the five tests within any of the four assessments.

## 7 References and versions

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