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Supplementary material for the paper
“Identifying a threshold for the executive function advantage
in bilingual children”

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Variable manipulation in the Working Memory analysis

The justification for dividing the STM and WM scores by age is motivated by two considerations.

1. The first one is from a modelling point of view. With a relatively moderate-to-high correlation between the scores and age, the standard error of the parameter estimates are relatively unstable. If we include the (raw) scores and age in the model, the model orthogonalises the influence of each score and age, which means that they are forced to be interpreted as independent variables, when in fact they are not.
2. The second consideration is how to interpret the model parameters when the variables are correlated. For example, suppose we have (raw) STM score and age in the model, and the estimates for the STM score is 1 (one). From a purely mathematical point of view, we can say that an increase by one score would increase the odds ratio of having more number of digits recalled by 2.78 ($\exp(1)$), given that the other predictors are fixed. However, this is unrealistic since older children are expected to be able to recall more digits in the experiment. This is why when there are two correlated variables in the model, the standard errors of the parameter estimates are higher compared to those of independent variables. In other words, when two variables are correlated, the uncertainty of the estimates are also higher to reflect that the interpretation of one variable cannot be separated from the other variable. Hence, the interpretation of the STM or WM score cannot be separated from age. To interpret the model, we would have to always say "As the STM score increases by one **and** age increases by 1 month, then..." for example, and would not be able to investigate the STM and WM scores independently. By dividing the scores with age, we are considering the 'slope' or the incremental 'rate' of the score to represent the short term memory, and not the scores

themselves. With this new variable, the interpretation can be made independent since the new variables represent STM and WM scores, regardless the age of the children, assuming linearity.

Profile of the children above the critical BPI threshold in the inhibition task

| Child | Age onset (full years) | Age (months) | Cumulative measures (equiv.months) | | Current measures (%) | | BPI |
|-------|---------------------------|-----------------|---------------------------------------|--------|-------------------------|--------|-------|
| | | | Input | Output | Input | Output | |
| BI6 | 1.00 | 79.00 | 43.00 | 43.00 | 0.47 | 0.47 | 61.00 |
| BI95 | 2.00 | 61.00 | 44.00 | 40.00 | 0.55 | 0.43 | 60.00 |
| BI25 | 3.00 | 74.00 | 45.00 | 42.00 | 0.23 | 0.15 | 62.00 |
| BI101 | 0.00 | 80.00 | 46.00 | 45.00 | 0.58 | 0.56 | 65.00 |
| BI9 | 1.00 | 66.00 | 46.00 | 39.00 | 0.63 | 0.50 | 61.00 |
| BI42 | 3.00 | 70.00 | 47.00 | 47.00 | 0.32 | 0.32 | 67.00 |
| BI58 | 0.00 | 63.00 | 47.00 | 47.00 | 0.75 | 0.75 | 67.00 |
| BI75 | 3.00 | 76.00 | 48.00 | 42.00 | 0.31 | 0.15 | 64.00 |
| BI32 | 3.00 | 66.00 | 48.00 | 36.00 | 0.40 | 0.00 | 60.00 |
| BI3 | 3.00 | 68.00 | 49.00 | 49.00 | 0.40 | 0.40 | 70.00 |
| BI103 | 2.00 | 71.00 | 49.00 | 49.00 | 0.54 | 0.54 | 70.00 |
| BI14 | 3.00 | 68.00 | 50.00 | 48.00 | 0.43 | 0.38 | 70.00 |
| BI91 | 2.00 | 84.00 | 51.00 | 51.00 | 0.45 | 0.45 | 72.00 |
| BI90 | 3.00 | 67.00 | 51.00 | 50.00 | 0.49 | 0.45 | 72.00 |
| BI12 | 2.00 | 75.00 | 51.00 | 38.00 | 0.53 | 0.27 | 63.00 |
| BI78 | 3.00 | 68.00 | 53.00 | 48.00 | 0.53 | 0.38 | 72.00 |
| BI53 | 4.00 | 70.00 | 54.00 | 54.00 | 0.29 | 0.29 | 77.00 |
| BI11 | 3.00 | 78.00 | 54.00 | 54.00 | 0.44 | 0.44 | 77.00 |
| BI39 | 3.00 | 68.00 | 54.00 | 54.00 | 0.55 | 0.55 | 77.00 |
| BI33 | 3.00 | 68.00 | 55.00 | 55.00 | 0.60 | 0.60 | 78.00 |
| BI68 | 3.00 | 61.00 | 56.00 | 56.00 | 0.79 | 0.79 | 80.00 |
| BI15 | 1.00 | 74.00 | 57.00 | 49.00 | 0.73 | 0.59 | 75.00 |
| BI31 | 3.00 | 68.00 | 58.00 | 52.00 | 0.68 | 0.50 | 78.00 |
| BI7 | 4.00 | 66.00 | 60.00 | 58.00 | 0.64 | 0.53 | 84.00 |
| BI98 | 4.00 | 66.00 | 60.00 | 62.00 | 0.68 | 0.77 | 87.00 |
| BI34 | 3.00 | 67.00 | 60.00 | 60.00 | 0.79 | 0.79 | 85.00 |
| BI30 | 3.00 | 77.00 | 62.00 | 62.00 | 0.64 | 0.64 | 88.00 |
| BI52 | 2.00 | 68.00 | 63.00 | 63.00 | 0.89 | 0.89 | 89.00 |
| BI80 | 2.00 | 73.00 | 66.00 | 66.00 | 0.85 | 0.85 | 94.00 |
| BI81 | 3.00 | 71.00 | 67.00 | 67.00 | 0.88 | 0.88 | 95.00 |
| BI97 | 5.00 | 71.00 | 68.00 | 66.00 | 0.74 | 0.54 | 95.00 |
| BI17 | 4.00 | 74.00 | 68.00 | 68.00 | 0.75 | 0.75 | 96.00 |
| BI36 | 4.00 | 75.00 | 69.00 | 63.00 | 0.76 | 0.57 | 94.00 |

Table 1

Children above the critical bilingualism threshold for enhanced performance in the Simon task

The table shows the extent of the variability among the children predicted to show an inhibition advantage (*ceteris paribus*) and illustrates how specific values on the BPI link various types of profiles in terms of bilingual experience. It also shows that this variability is limited in the subgroup identified (i.e. those above the critical threshold). For instance, the table shows that child BI32, who has no current output in the home language, initially had a monolingual period in the home language.

The variability observed among the group above the BPI threshold shows that there are different ways of achieving sufficient bilingual experience. We believe it is a strength of our measure to be able to capture that.

On the exclusion of Participant from the random effect structure in the Cox model

Random effects must be included in a linear regression model if the data violates the independence assumption (Hougaard, 2000). In our case, the serial correlation between test items requires that item is included as a random effect. Since the item has been taken into account in the model, the dependencies between items are no longer present in the residuals. This is a mathematical fact, in which the residuals by construction are orthogonal to the predictor space (where the items are one of them). In our data, there is no correlation structure between participants (e.g. shared genetic profile) that would make it obligatory to include participant as a random effect.

As expected, there is systematic between-subject variability in our data, and our model seeks to **explain** that variability through the participant-related variables (age, SES, BPI score, and the interaction between bilingualism and SES). What predicts the “baseline” performance of each participant (modelled as time to a correct response) is the **combination** of these participant-related variables. As these variables are measured on fine-grained gradients, their combination is very close to identifying individual participants — hence the collinearity between participant and the participant-related variables.

If we were to include participant as a random effect in our model, given the collinearity between participant and the participant-related variables, it would capture most of the variability currently captured by the (participant-related) fixed effects, which would become mostly non-significant. The resulting model would be of little scientific value, as the possible causes for the participant-induced variability would not be identified.

References

Hougaard, P. (2000). *Analysis of multivariate survival data*. New York: Springer.