

Dependency learning: comparing adults and children

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Comparisons between children and adults

In this final analysis we evaluate differences between the adults (Experiment 1) and the children results (Experiment 2). In particular, we focused on the effect of main interest to evaluate implicit learning; i.e. the slowdown in reaction times in the transfer block (Block 7) relative to Block 6. Also we tested for learning differences comparing the conditional effects for Block 1 and Block 6; we observed evidence for learning differences in the results section of Experiment 1 and Experiment 2. To compare the data from adults and children we pooled the serial reaction-time data from both experiments and extracted the data from Blocks 1, 6 and 7.

This analysis was largely similar to the reaction-time models reported earlier: reaction times were modelled in Bayesian linear mixed-effects models. Reaction times for elements that were not part of an adjacent or nonadjacent dependency were included in the model as baseline. Model predictors were Age Group (levels: adults, children), Dependency (levels: dependency, baseline), Adjacency (levels: adjacent, nonadjacent), Learning Block (levels: 1, 6), Transfer Block (levels: 6, 7), and all by-Dependency and by-Adjacency interactions with Group and Block. All predictors were sum-coded following Schad et al. (2020). Reaction time data were fitted with a shifted-lognormal distribution, random intercepts for each stimulus image, and participants with by-participant slope adjustments for all main effects and interactions.

In addition to the parameter estimates as in the previous results sections, we used the posterior to calculate the standardised effect sizes δ , defined as $\delta = \frac{\mu}{\sigma}$, where μ is the parameter value of the effect of interest and σ is the standard deviation. The effect size was calculated to allow comparisons across age group (Wagenmakers et al., 2010). Because the standard deviation is necessary to calculate the effect size, we specified the model with two different variance components, one for the children group and one for the adults group as the

population standard deviation is likely to be different for each group (Baguley, 2009).

For the effect sizes, we determined the region of practical equivalence (henceforth, ROPE) to assess the uncertainty of the effect size (Makowski et al., 2019). The ROPE is the range of values that are practically equivalent to a null effect (see e.g. Kruschke, 2010, 2011). For the effect size we set the ROPE to be -0.1 and 0.1 (Kruschke, 2018) which is the range of negligible effect sizes (Cohn, 1988). The value returned is the proportion of posterior samples (of the effect size) that falls inside the ROPE. In other words, the ROPE value indicates the extent to which the posterior cannot rule out an negligible effect. A meaningful effect size should have a small proportion of posterior samples within the ROPE.

Table 1 summaries the modelling outcome for the serial reaction-time data. We found compelling evidence for longer reaction times for children compared to adults. Also, overall we found evidence that adjacent dependencies were responded to faster than nonadjacent dependencies. Reaction times for Block 6 were shorter than for Block 1 and were followed by a slowdown for Block 7. Further evidence was found for two-way interactions of Age Group and Dependency, and Age Group and Learning Block. Importantly, we found evidence for a three-way interaction of Dependency by Transfer Block and Age Group. There was negligible evidence for all remaining predictors. The variance estimate for the children group ($\hat{\sigma} = 0.37$, 95% HPDI[0.36, 0.38]) was larger than the variance estimate for the adults group ($\hat{\sigma} = 0.32$, 95% HPDI[0.31, 0.32]).

Table 1

Age-group comparison for serial reaction-time data. Estimated parameter values (in msec) for main effects and interactions of Learning Block (levels: 1, 6) and Transfer Block (levels: 6, 7), Age Group (levels: adults, children), Dependency (levels: dependency, baseline), Adjacency (levels: adjacent, nonadjacent).

Predictor	$\hat{\mu}$	95% HPDI	$P(\hat{\mu} < 0)$
Main effects			
Age Group	-327	[-383, -270]	>.999
Dependency	3	[-30, 34]	.447
Adjacency	-23	[-41, 0]	.977
Block: Learning	217	[189, 243]	<.001
Block: Transfer	-35	[-54, -19]	>.999
Two-way interactions			
Age \times Dependency	-64	[-88, -41]	>.999
Age \times Adjacency	-12	[-30, 8]	.877
Age \times Block (Learning)	69	[49, 92]	<.001
Age \times Block (Transfer)	-2	[-18, 13]	.616
Dependency \times Block (Learning)	4	[-11, 22]	.278
Dependency \times Block (Transfer)	-16	[-40, 5]	.928
Adjacency \times Block (Learning)	-6	[-19, 8]	.757
Adjacency \times Block (Transfer)	2	[-14, 19]	.415
Three-way interactions			
Dependency \times Block (Learning) \times Age	-3	[-19, 14]	.618
Dependency \times Block (Transfer) \times Age	-25	[-41, -7]	.997
Adjacency \times Block (Learning) \times Age	3	[-11, 17]	.327
Adjacency \times Block (Transfer) \times Age	-1	[-14, 15]	.499

Note. $\hat{\mu}$ = most probable parameter value; 95% HPDI = interval containing 95% of the probability mass; $P(\hat{\mu} < 0)$ = probability of the true parameter value being smaller than 0; \times = interaction.

Figure 1 illustrates the modelled serial reaction-time data illustrating the speedup from Block 1 to Block 6 and the slowdown from Block 6 to Block 7 for the adult and the children group. The slowdown from Block 6 to 7 was tested within Age Group and Dependency to gain further insight into the source of the three-way interaction. Reported are the effect sizes for each comparison.

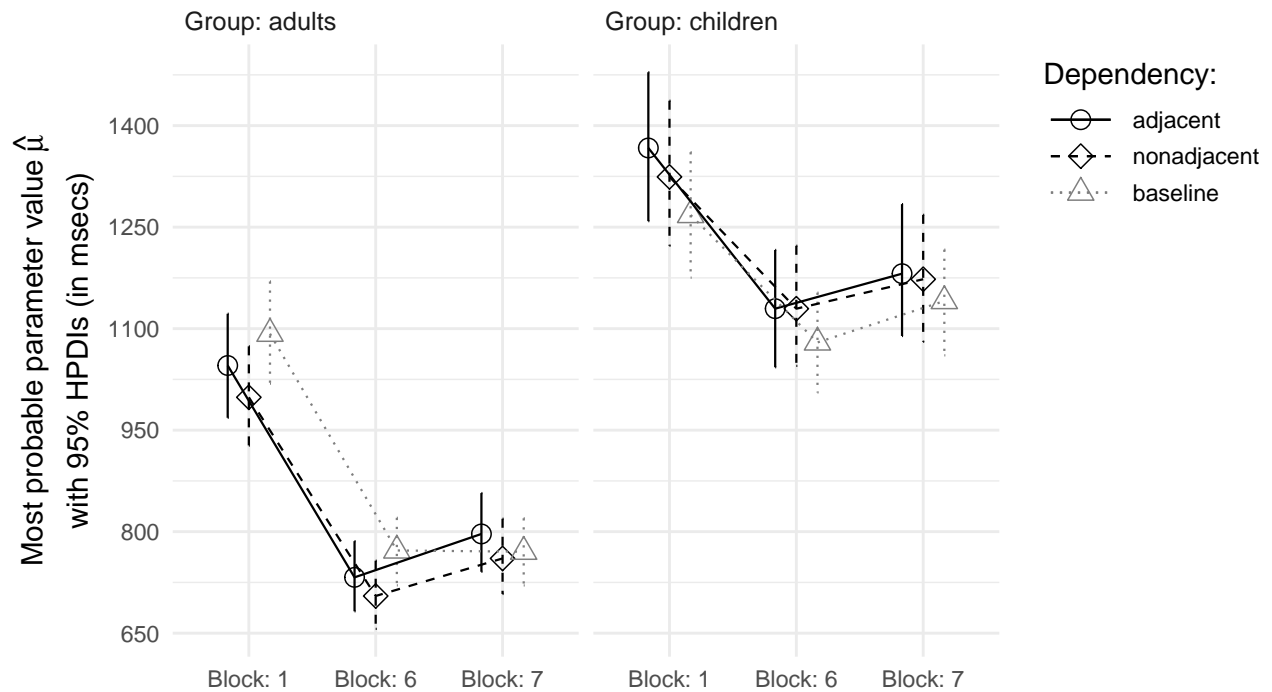


Figure 1

Modelled serial reaction-time data (group comparison). Reaction-time data are shown by age group for the first block compared to Block 6 (learning) and Block 6 compared to the final block (transfer). Shown are the modelled reaction-time data with 95% HPDI (in msecs) for both adjacency conditions (adjacent, nonadjacent) and the baseline condition.

First, we inspected the Age Group by Dependency (levels: dependency, baseline) interaction in differences between dependency conditions and baseline trials, across blocks. For the adult group we found a small effect ($\hat{\delta} = -0.16$, 95% HPDI[-0.25, -0.09], ROPE = 0%) showing longer reaction times for baseline trials compared to dependencies. In contrast we

found longer reaction times for dependencies compared to baseline trials for the children group; the size of this effect was however negligible to small ($\hat{\delta} = 0.09$, 95% HPDI[0.02, 0.17], ROPE = 61%).

Second, we inspected the Age Group by Learning Block (levels: Block 1, Block 6) interaction in reaction time comparisons within Age Group, across dependency types. Both groups showed evidence for a learning effect, i.e. shorter reaction times in Block 6; the effect size for the adults group was large to very large ($\hat{\delta} = -1.10$, 95% HPDI[-1.21, -0.99], ROPE = 0%) and small to medium for the children group ($\hat{\delta} = -0.47$, 95% HPDI[-0.57, -0.35], ROPE = 0%).

Finally, we observed an interaction of Dependency (levels: dependency, baseline), Transfer Block (levels: Block 6, Block 7), and Age Group. For the adult group, we observed a small effect for a slowdown from Block 6 to 7 in the dependency condition ($\hat{\delta} = 0.26$, 95% HPDI[0.11, 0.39], ROPE = 0) but a negligible slowdown effect in baseline trials ($\hat{\delta} = -0.01$, 95% HPDI[-0.08, 0.07], ROPE = 100). For the children group, we observed a negligible to small slowdown effect in the dependency condition ($\hat{\delta} = 0.11$, 95% HPDI[-0.02, 0.25], ROPE = 42.18) and a small slowdown effect for the baseline condition ($\hat{\delta} = 0.14$, 95% HPDI[0.07, 0.23], ROPE = 5.60).

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