Does the speed of automatization predict differences in linguistic ability in children with developmental language disorder?

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INTRODUCTION

Question: How do cognitive abilities predict differences in children’s linguistic development?

The aim of this study is to establish cognitive predictors of group membership between children with typically developing language and children with language difficulties (developmental language disorder).

We investigate four cognitive predictors:

• non-verbal intelligence
• working memory
• speed of automatization
• implicit statistical learning

Language measures:

• Grammar
• Vocabulary
• Syntactic complexity and fluency/dysfluency measures

METHODS

Individual differences design, comprising:

• children with typically developing language (language typical: LT)
• children with developmental language disorder (DLD), classified by scores of <1.25 SDs or more below the mean on standardized language measures of receptive and expressive language ability.

77 participants (mean age: 8.3 years)
• 54 language typical children
• 23 children with DLD

Hybrid method of data collection:
• We posted children a Tower of Hanoi puzzle in the post in advance of the first session.
• 3 online sessions via Zoom.

Session 1:
Children completed the Multiple-trial Tower of Hanoi task (MToH):
• 25 trials of the MToH
• 5 trials – secondary task

SESSIONS 2 AND 3:
Children completed a battery of language and cognitive tasks:

Session 2:
Narrative task ‘Ping, Where Are You? ’ (Mayo, 1969)
Test for the Reception of Grammar (Brown, 2000)
Brown’s Coloured Progressive Matrices (Wexler, 1984)
Backwards Colour Span Task (Riches, 2012)
Embedded triplets task adapted from Segalowitz & Simpson, 1995

Session 3:
The British Picture Vocabulary Scale 3 (Dunn, Dunn & Stiles, 2003)
Sentence grammaticality judgement task (Wexler, 1984)

RESULTS

Summary statistics and effect sizes (Cohens d) are reported in Table 1.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Mean: LT</th>
<th>Mean: DLD</th>
<th>Effect size d (p-value)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Language measures</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Receptive grammar</td>
<td>17.07 (1.39)</td>
<td>7.26 (1.14)</td>
<td>0.57 (p&lt;0.001)</td>
</tr>
<tr>
<td>Productive grammar</td>
<td>52.97 (4.43)</td>
<td>22.03 (9.77)</td>
<td>2.03 (p&lt;0.001)</td>
</tr>
<tr>
<td>Receptive vocabulary</td>
<td>129.04 (11.52)</td>
<td>131.75 (23.54)</td>
<td>0.25 (p&lt;0.001)</td>
</tr>
<tr>
<td>Productive vocabulary</td>
<td>36.57 (17.73)</td>
<td>26.38 (8.83)</td>
<td>0.46 (p&lt;0.001)</td>
</tr>
<tr>
<td>Substitution rate</td>
<td>1.27 (0.10)</td>
<td>1.10 (0.06)</td>
<td>0.15 (p&lt;0.001)</td>
</tr>
<tr>
<td>MFL mcurrently</td>
<td>8.88 (0.49)</td>
<td>6.62 (1.18)</td>
<td>0.19 (p&lt;0.001)</td>
</tr>
<tr>
<td>Speech rate</td>
<td>2.86 (0.45)</td>
<td>2.13 (0.39)</td>
<td>0.11 (p&lt;0.001)</td>
</tr>
<tr>
<td>Dysfluency</td>
<td>16.80 (1.73)</td>
<td>20.49 (1.10)</td>
<td>0.36 (p&lt;0.001)</td>
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<tr>
<td>Cognitive measures</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nonverbal IQ</td>
<td>29.36 (11.53)</td>
<td>21.71 (3.23)</td>
<td>0.44 (p&lt;0.001)</td>
</tr>
<tr>
<td>Working memory</td>
<td>15.05 (10.89)</td>
<td>13.61 (5.36)</td>
<td>0.18 (p&lt;0.001)</td>
</tr>
<tr>
<td>Implicit learning</td>
<td>51.02 (10.41)</td>
<td>50.45 (8.58)</td>
<td>0.03 (p&lt;0.001)</td>
</tr>
<tr>
<td>Coefficient of variation</td>
<td>0.84 (0.09)</td>
<td>0.89 (0.05)</td>
<td>0.01 (p&lt;0.001)</td>
</tr>
</tbody>
</table>

Table 1: Summary statistics (Mean and SD) and Cohens d (raw or z-scored).

The measure of the speed of automatization (CV) is expressed as a coefficient of variation (calculated by dividing the SD by the mean number of moves on the MToH), where automatization reflects a decrease in the coefficient of variation (following Segalowitz & Segalowitz, 1993). Strongly automatized behaviours show very little within-participation variation.

Logistic regression was used to analyse the relationship between language difficulty (language typical children, coded as ‘0’ and children with DLD, coded as ‘1’), and four cognitive predictors: non-verbal IQ, working memory, implicit learning, and the speed of automatization. The final model is shown in Table 2.

DISCUSSION

• The two groups show significant differences in cognitive abilities and language measures.
• Nonverbal IQ is the strongest predictor of language outcomes in our sample, followed by working memory and the speed of automatization.
• 61% of children in the DLD group have a combination of low nonverbal IQ, low working memory, and slow speed of automatization, in comparison to median scores of the LT group.
• These findings suggest that language difficulties in children are additive, caused by a combination of cognitive factors which impact linguistic outcomes.

Children with DLD showed slower automatization on the MToH task. This could suggest difficulties with proceduralization, as previous literature has shown.

CONTACT INFORMATION

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REFERENCES


TAKING HOME MESSAGE

Non-verbal IQ, working memory, and automatization are significant predictors of group membership.

Children with language difficulties show slower speed of automatization as reflected in the MToH task.

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