Importance of Multidimensional Assessment to Refine Subtypes of Developmental Coordination Disorder

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Objectives

The DSM-IV-TR criteria for Developmental Coordination Disorder (DCD) involve a marked impairment in the development of motor coordination although visuo-spatial, digital and visuo-motor perception, neuromuscular tone, qualitative and quantitative measures of gross and fine motor coordination related impairments might be used to isolate three main subtypes of DCD/dyspraxia: ideomotor (IM), visuo-spatial and constructional (VSC), and a mix (MX) group sharing common impairments with additional comorbidities.[1,2] This study focus on **isolating specific markers of coordination disorder and their interaction in mix** *vs.* **pure form of dyspraxia**.

Methods

Data were collected on N=63 children with DCD aged between 5 and 15 years (median, 8.1 years; 83% of males) enrolled on DSM-IV criteria and IQ in the expected range, with no previous assessment, no medication and no therapy follow-up. Overall, 40% were diagnosed as suffering from mix dyspraxia. For each subject, binary-scored (pass/fail) responses were available for a set of 49 items covering tone, praxia, perceptions, as well as visual, motor, perceptuo-motor, and general performance.
Tree-based bagged classifiers, logic forest[3] and bagged logic regression,[4] were used to highlight relevant markers among those items. Model calibration was done on a training sample using bootstrap resampling while predictive performance (Accuracy, Sensitivity and Specificity) was assessed on a holdout sample with a split ratio of 0.7/0.3.

Results

Patients' characteristics are summarized in the Table below. Neither average IQ levels nor mean age or gender distribution did show significant differences between the training and validation sample. Frequency of impairments for each clinical group is summarized in **Fig. A**).

	N	Training N=45	Validation N=18	Combined N=63
Type: MX	63	40% (18)	39% (7)	40% (25)
Gender: Male	63	87% (39)	72% (13)	83% (52)
Age	63	7.1 8.6 10.1	6.3 8.0 11.0	6.8 8.1 10.4
FIQ	62	86 100 117	88 97 108	86 100 115
PIQ	62	75 93 105	73 86 108	74 90 105
VIQ	62	92 114 124	94 103 118	92 110 124

Three-number summaries are lower quartile, median, and upper quartile.

N is the number of non--missing values.

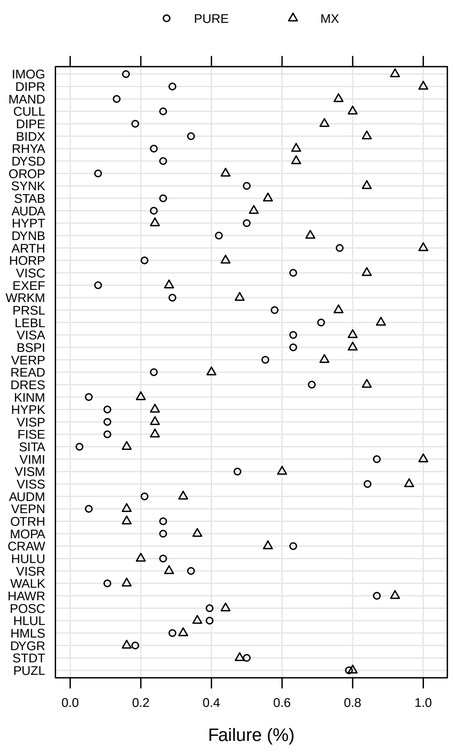


Figure A. Distribution of impairments for each clinical group (all patients), sorted by relative difference of failure. (PURE=VSC+IM)

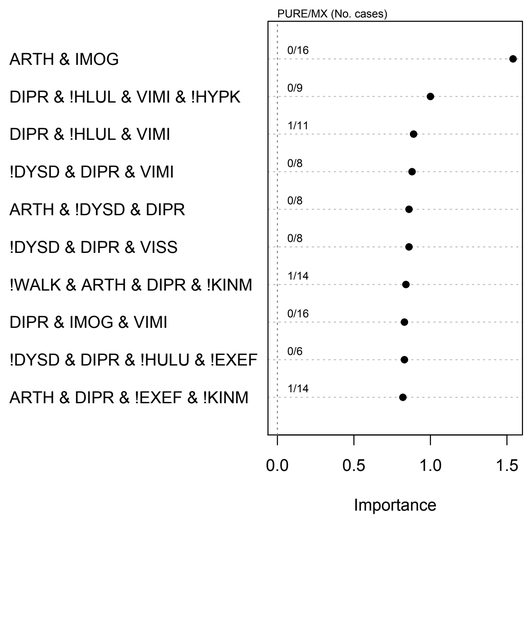
On the training sample, univariate group comparisons with Pearson's χ^2 tests, controlling for False Discovery Rate of 5% (Benjamini and Hochberg's procedure) indicate that four items show significant difference in terms of frequency of failure: IMOG (76.2% of difference), DIPR (71.1%), MAND (62.8%), DIPE (53.6%).

SITA Sitting alone, CRAW Crawling, WALK Walking alone, FISE First sentences (language), OTRH Otorhinolaryngologia, VISR Visual refraction, LEBL Lego blocks, PUZL Puzzles, ARTH Arithmetic, READ Reading/spelling, HAWR Hand writing, DYGR Dysgraphia, HYPT Hypotonia, MOPA Motor pathway, SYNK Synkinesis, DYSD Dysadiadochokinesis, STDT Standing tone, **DIPR Digital praxia**, BIDX Bimanual dexterity, PRSL Praxia slowness, **IMOG Imitation of gestures**, OROP Orofacial praxia, DRES Dressing skill, **DIPE Digital perception**, VISP Visual perception, STAB Static balance, DYNB Dynamic balance, CULL Coordination between upper and lower limbs, POSC Postural control, HLUL Homogeneity tonic laterality upper/lower limbs, HMLS Homogeneity manual laterality spontaneous psychomotor, HULU Homogeneity usual laterality upper/lower limbs, **MAND Manual dexterity**, BSPI Body spatial integration, RHYA Rhythmic adaptation, VIMI Visual motor integration, VISS Visual spatial structuration, VISC Visual spatial constructional, EXEF Executive function, AUDM Auditivo memory, WRKM Work memory, KINM Kinaesthetic memory (perception), VISM Visual spatial memory, AUDA Auditivo attention, VISA Visual spatial attention, HYPK Hyperkinesia, HORP Horizontal pursuit, VERP Vertical pursuit, VEPN Visual evocated potentials (neurovisual).

According to the Logic Forest algorithm (built upon 100 trees), the five most important predictors appeared to be (with normalized predictor importance): Imitation of gestures (1), Digital praxia (0.64), Arithmetic (0.18), Visual motor integration (0.03), and Digital perception (0.02). This is in agreement with our previous study where Random Forests and sparse PLS regression were used to isolate the most contributing predictors to three clinical subgroups.[5] Among the ten most important interactions we found items such as arithmetic, digital praxia, visuo-motor related abilities, dysadiadochokinesis, or executive function (**Fig. B**).

Figure B. Measure of variable importance* from logic forest (training sample only).

*! means logical negation; e.g. !DYSD & DIPR ≡ no failure for Dysadiadochokinesis and failure for Digital praxia.



Predictive accuracy on the validation sample was good for both methods, with out-of-bag (OOB) error rate below 9% in each case. Compared to Random Forests (6.7% OOB error), they showed higher accuracy and better sensitivity, with only two PURE dyspraxic patients classified as MX.

	Accuracy (95% CI)	Sensitivity	Specificity
logforest	0.889 (0.653, 0.986)	0.818	1.000
logbag	0.889 (0.653, 0.986)	0.818	1.000
rf	0.833 (0.586, 0.964)	0.727	1.000

logforest: ensemble classifier of logic regression models;

logbag: bagged version of logic regression; rf Random Forests.

The two misclassified patients suffered from visual and constructional dyspraxia, confirming earlier results.[5] These two methods further demonstrate that comorbidities help to distinguish between the two clinical groups.

Conclusions

Taylored follow-up of patients presenting with DCD should consider the specificity of visuo-spatial, neuromotor and neuropsychological impairments whose co-occurence allow to define different subtypes of DCD. Ensemble learning methods prove to be useful statistical tools to unravel complex relationships between clinical markers.

References:

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