

1 **Neurocognitive reorganization between crystallized intelligence,** 2 **fluid intelligence and white matter microstructure in two age-** 3 **heterogeneous developmental cohorts**

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13 **Abstract**

14 Despite the reliability of intelligence measures in predicting important life outcomes such as
15 educational achievement and mortality, the exact configuration and neural correlates of
16 cognitive abilities remain poorly understood, especially in childhood and adolescence.
17 Therefore, we sought to elucidate the factorial structure and neural substrates of child and
18 adolescent intelligence using two cross-sectional, developmental samples (CALM: N=551,
19 age range: 5-18 years, NKI: N=337, age range: 6-18 years). In a preregistered analysis, we
20 used structural equation modelling (SEM) to examine the neurocognitive architecture of
21 individual differences in childhood and adolescent cognitive ability. In both samples, we
22 found that cognitive ability in lower and typical-ability cohorts is best understood as two
23 separable constructs, crystallized and fluid intelligence, which became more distinct across
24 development. Further analyses revealed that white matter microstructure, most prominently
25 the superior longitudinal fasciculus, was strongly associated with crystallized (gc) and fluid
26 (gf) abilities. Finally, we used SEM trees to demonstrate evidence for age differentiation-
27 dedifferentiation of gc and gf and their white matter substrates such that the relationships
28 among these factors dropped between 7-8 years before increasing around age 10. Together,
29 our results suggest that shortly before puberty marks a pivotal phase of change in the
30 neurocognitive architecture of intelligence.

31 **Keywords**

32 Age differentiation-dedifferentiation; Crystallized intelligence; Fluid intelligence; White matter;
33 Structural equation modelling

34

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39 **1. Introduction**

40

41 Intelligence measures have repeatedly been shown to predict important life

42 outcomes such as educational achievement (Deary et al., 2007) and mortality (Calvin et al.,

43 2011). Modern investigations of intelligence began over 100 years ago, when Spearman first

44 proposed *g* (for 'general intelligence') as the underlying factor behind his positive manifold of

45 cognitive ability and established intelligence as a central theme of psychological research

46 (Spearman, 1904). Cattell proposed a division of Spearman's *g*-factor into two separate yet

47 related constructs, crystallized (gc) and fluid (gf) intelligence (Cattell, 1967). Cattell

48 suggested that gc represents the capacity to effectively complete tasks based on acquired

49 knowledge and experience (e.g. arithmetic, vocabulary) whereas gf refers to one's ability to

50 solve novel problems without task-specific knowledge, relying on abstract thinking and

51 pattern recognition (see also Deary et al., 2010).

52 Current understanding of lifespan trajectories of gc and gf using cross-sectional

53 (Horn and Cattell, 1967) and longitudinal (McArdle et al., 2000; Schaie, 1994) cohorts

54 indicates that gc slowly improves until late age while gf increases into early adulthood before

55 steadily decreasing. However, the majority of the literature on individual differences between

56 gc and gf has focused on early to late adulthood. As a result, considerably less is known

57 about the association between gc and gf in childhood and adolescence (but see Hülür et al.,

58 2011).

59 There has, however, been a recent rise in interest in this topic in child and adolescent

60 samples. For instance, research on age-related differentiation and its inverse, age

61 dedifferentiation, in younger samples has greatly expanded since first being pioneered in the

62 middle of the 20th century (Garrett, 1946). According to the age differentiation hypothesis,

63 cognitive factors become less correlated (more differentiated) with increasing age. For

64 example, the relationship (covariance) between gc and gf would decrease as children age

65 into adolescence, suggesting that cognitive abilities increasingly specialize into adulthood. In

66 contrast, the age dedifferentiation hypothesis predicts that cognitive abilities become more

67 strongly related (less differentiated) throughout development. In this case, gc and gf

68 covariance would increase between childhood and adolescence, potentially indicating a

69 strengthening of the *g*-factor across age. However, despite its increased attention in the

70 literature, the debate remains unsolved as evidence in support of both hypotheses has been

71 found (Bickley et al., 1995; de Mooij et al., 2018; Gignac, 2014; Hülür et al., 2011; Juan-

72 Espinosa et al., 2000; Tideman and Gustafsson, 2004). Together, this literature highlights

73 the importance of a lifespan perspective on theories of cognitive development, as neither

74 age differentiation nor dedifferentiation may be solely able to capture the dynamic changes

75 that occur from childhood to adolescence and (late) adulthood (Hartung et al., 2018).

76 The introduction of non-invasive brain imaging technology has complemented
77 conventional psychometric approaches by allowing for fine-grained probing of the neural
78 bases of human cognition. A particular focus in developmental cognitive neuroscience has
79 been the study of white matter using techniques such as diffusion-weighted imaging, which
80 allows for the estimation of white matter microstructure (Wandell, 2016). Both cross-
81 sectional and longitudinal research in children and adolescents using fractional anisotropy
82 (FA), a commonly used estimate of white matter integrity, have consistently revealed positive
83 correlations between FA and cognitive ability using tests of working memory, verbal and
84 non-verbal performance (Krogsrud et al., 2018; Peters et al., 2014; Tamnes et al., 2010;
85 Urger et al., 2015). In particular, recent research has found associations between the corpus
86 callosum (Navas-Sánchez et al., 2014; Westerhausen et al., 2018) association fibers (e.g.
87 inferior longitudinal fasciculus, see Peters et al., 2014), the superior longitudinal fasciculus
88 (Urger et al., 2015), and differences in cognitive ability, suggesting the importance of white
89 matter integrity across large coordinated brain networks for high cognitive performance.
90 However, interpretations of these studies are limited due to restricted cognitive batteries
91 (e.g. small number of tests used) and a dearth of theory-driven statistical analyses (e.g.
92 structural equation modelling).

93 For these reasons, several outstanding questions in the developmental cognitive
94 neuroscience of intelligence remain: 1) Are the white matter substrates underlying
95 intelligence in childhood and adolescence best understood as a single global factor or do
96 individual tracts provide specific contributions to gc and gf?, 2) If they are specific, are the
97 tract contributions identical between gc and gf?, and 3) Does this brain-behavior mapping
98 change in development (e.g. age differentiation/dedifferentiation or both)?

99 To examine these questions, our preregistered hypotheses are as follows:

- 100 1) gc and gf are separable constructs in childhood and adolescence. More
101 specifically, the covariance among scores on cognitive tests are more adequately
102 captured by the two-factor (gc-gf) model as opposed to a single-factor (e.g. g)
103 model.
- 104 2) The covariance between gc and gf changes (decreases) across childhood and
105 adolescence.
- 106 3) White matter tracts make unique complementary contributions to gc and gf.
- 107 4) The contributions of these tracts to gc and gf change (decrease) with age.

108 To address these questions, we examined the relationship between gc and gf in two
109 large cross-sectional child and adolescent samples. The first is the Centre for Attention,
110 Learning and Memory (CALM, see Holmes et al., 2019). This sample, included in our
111 preregistration, was recruited atypically (see Methods for more detail) and generally includes
112 children with slightly lower cognitive abilities than age-matched controls. To examine

113 whether findings from CALM would generalize to other samples, we also conducted non-
114 preregistered analyses on the Nathan Kline Institute (NKI) Rockland Sample, a cohort with
115 similar population demographics to the United States (e.g. race and socioeconomic status,
116 see Table 1 of Noonan et al., 2012). All analyses were carried out using structural equation
117 modelling (SEM), a multivariate statistical framework combining factor and path analysis to
118 examine the extent to which causal hypotheses concerning latent (unobserved, e.g. g) and
119 manifest (observed, e.g. cognitive tests scores) variables (Schreiber et al., 2006) are in line
120 with the observed data. Taken together, this paper sought to investigate the relationship
121 between measures of intelligence (gc and gf) and white matter connectivity in typically and
122 atypically (struggling learners) developing children and adolescents.

123
124 **2. Methods**

125
126 *2.1.1 Participants*

127
128 For the CALM sample, we analyzed the most recent data release (N=551; 170
129 female, 381 male¹; age range=5.17-17.92 years) at the time of preregistration (see
130 <https://aspredicted.org/5pz52.pdf>). Participants were recruited based on referrals made for
131 possible attention, memory, language, reading and/or mathematics problems (Holmes et al.,
132 2019). Participants with or without formal clinical diagnosis were referred to CALM.
133 Exclusion criteria included known significant and uncorrected problems in vision or hearing
134 and a native language other than English. A subset of participants completed MRI scanning
135 (N=165; 56 female, 109 male; age range=5.92-17.92 years). For more information about
136 CALM, see <http://calm.mrc-cbu.cam.ac.uk/>.

137 Next, to assess the generalizability of our findings in CALM, we used a non-
138 preregistered subset of the data from the Nathan Kline Institute (NKI) Rockland Sample
139 (cognitive data: N=337; 149 female, 188 male; age range=6.12-17.94 years; neural data:
140 N=65; 27 female, 38 male; age range=6.97-17.8 years). This multi-institutional initiative
141 recruited a lifespan (aged between 6 and 85 years), community-ascertained sample (Nooner
142 et al., 2012). We chose this sample due to its representativeness (demographics resemble
143 those of the United States population) and the fact that its cognitive battery assessments
144 closely-matched CALM. For more information about the NKI Rockland Sample and its
145 procedures, see <http://rocklandsample.org/>. Also see Fig. 1 for age distributions of CALM

¹ Gender was coded as either female or male. However, it should be noted that participants might identify themselves as 'Other', which, to our knowledge, was not an option according to the biographical produces used in either sample.

146 and NKI. These same two cohorts were used in a recent paper to address a distinct set of
147 questions (Fuhrmann et al., 2019).

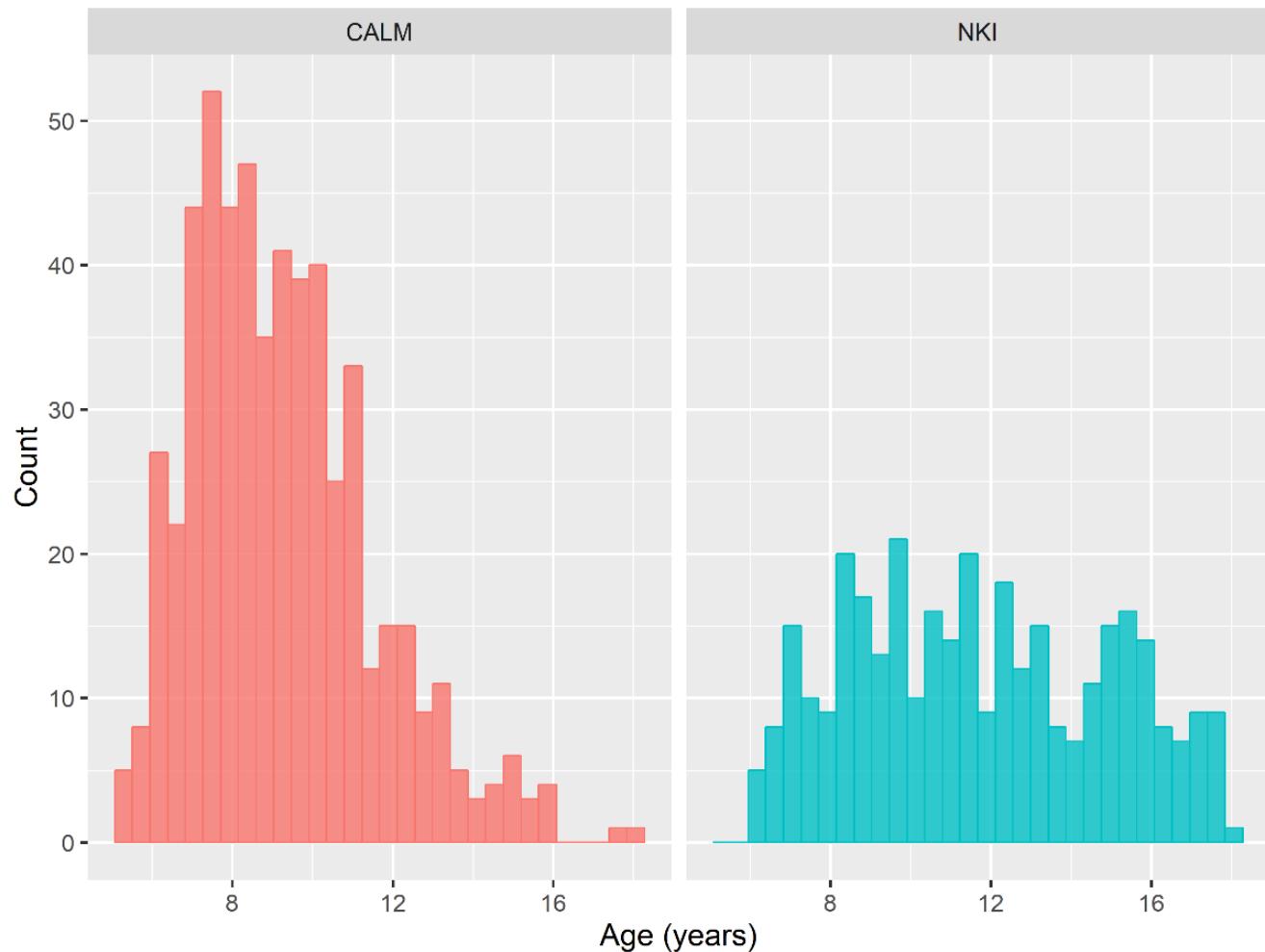


Fig. 1. Histograms of age distributions for CALM and NKI Rockland samples.

148 **2.1.2 Statistical analyses**

149

150 We used structural equation modelling (SEM), a multivariate approach that combines
151 latent variables and path modelling to test causal hypotheses (Schreiber et al., 2006) as well
152 as SEM trees, which combine SEM and decision tree paradigms to simultaneously permit
153 exploratory and confirmatory data analysis (Brandmaier et al., 2013).

154 We performed structural equation modelling (SEM) using the lavaan package version
155 0.5-22 (Rosseel, 2012) in R (R Core Team, 2018) and versions 2.9.9 and 0.9.12 of the R
156 packages OpenMx (Boker et al., 2011) and semtree (Brandmaier et al., 2013), respectively.
157 To account for missing data and deviations from multivariate normality, we used robust full
158 information maximum likelihood estimator (FIML) with a Yuan-Bentler scaled test statistic
159 (MLR) and robust standard errors (Rosseel, 2012). We evaluated overall model fit via the

160 (Satorra-Bentler scaled) chi-squared test, the comparative fit index (CFI), the standardized
161 root mean squared residuals (SRMR), and the root mean square error of approximation
162 (RMSEA) with its confidence interval (Schermelleh-Engel et al., 2003). Assessment of model
163 fit was defined as: CFI (acceptable fit 0.95-0.97, good fit >0.97), SRMR (acceptable fit 0.05-
164 .10, good fit <0.05), and RMSEA (acceptable fit 0.05-0.08, good fit <0.05). To determine
165 whether gc and gf were separable constructs, we compared a two-factor (gc-gf) model to an
166 single-factor (g) model. To investigate if the covariance between gc and gf differed across
167 ages, we conducted multiple group comparisons between younger and older participants
168 based on median splits (CALM split at 8.91 years yielding N=279 young and 272 old; NKI
169 split at 11.38 years into N=169 young and N=168 old). Doing so inevitably led to slightly
170 unbalanced numbers of participants with white matter data (CALM: young, N=60 & old,
171 N=105; NKI: young, N=19 & old, N=46). To test measurement invariance across age groups
172 (Putnick and Bornstein, 2016), we fit multigroup models (French and Finch, 2008),
173 constraining key parameters across groups. Model comparisons and deviations from
174 measurement invariance were determined using the likelihood ratio test and Akaike
175 information criterion (AIC, see Bozdogan, 1987).

176 To examine whether white matter tracts made unique contributions to our latent
177 variables we fit Multiple Indicator, Multiple Cause (MIMIC) models (Jöreskog and
178 Goldberger, 1975; Kievit et al., 2012). Lastly, we conducted a SEM tree analysis, a method
179 that combines the confirmatory nature of SEM with the exploratory framework of decision
180 trees (Brandmaier et al., 2013). SEM trees hierarchically and recursively partition data
181 (decision tree) according to covariates that explain the maximum difference in parameter
182 estimates of a theorized model (SEM). For each SEM tree analysis, a minimum sample size
183 of 100 was set for each node to aid estimation. Our use of this technique was twofold: 1)
184 Examine the robustness of findings based on the median age split, and 2) examine whether
185 white matter contributions differed across age groups of younger and older participants
186 (Hypothesis 4). Therefore, for our SEM tree analyses in CALM and NKI, we used age as a
187 continuous covariate.

188

189 2.1.3 Cognitive assessments: gc, gf, and working memory

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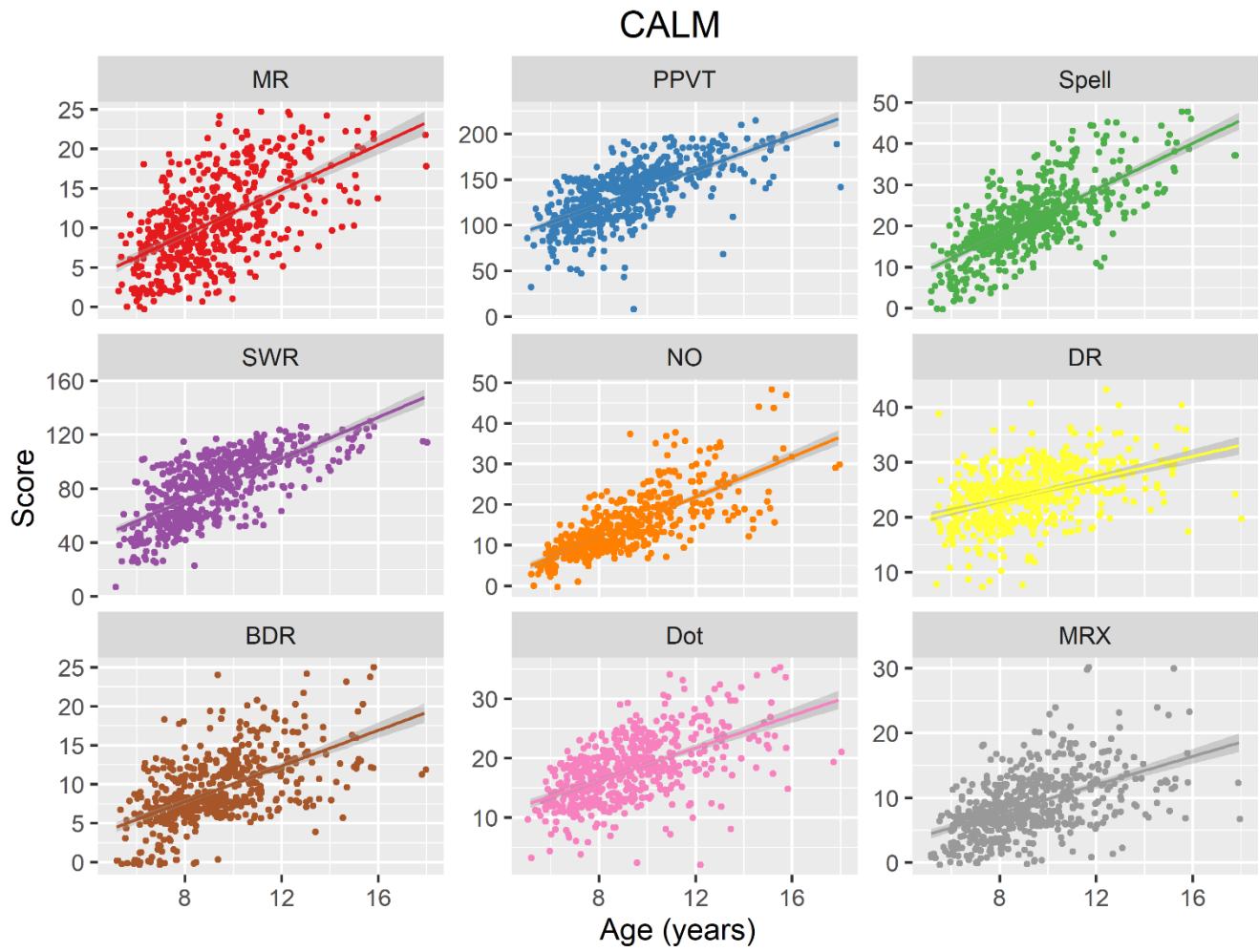
191 All cognitive data from the CALM sample were collected on a one-to-one basis by an
192 examiner in a dedicated child-friendly testing room. The test battery included a wide range of
193 standardized assessments of cognition and learning (Holmes et al., 2019). Participants were
194 given regular breaks throughout the session. Testing was divided into two sessions for
195 participants who struggled to complete the assessments in one sitting. For analyses of the
196 NKI Rockland Sample cohort, we matched tasks used in CALM except for the Peabody

197 Picture Vocabulary Test, Dot Matrix, and Mr. X, which were only available for CALM. For the
 198 NKI Rockland Sample, we included the N-Back task, which is not available in CALM (Nooner
 199 et al., 2012). In both samples, only raw scores obtained from assessments were included in
 200 analyses. Due to varying delays between recruitment and testing in NKI, we only used
 201 cognitive test scores completed no later than six months after initial recruitment. The
 202 cognitive tasks are further described in Table 1; the raw scores are depicted in Fig. 2.
 203

Cognitive Domain	Sample	Task and Description	Mean (sd) [range]	Missing Data %	Reference
Crystallized Ability (gc)	CALM	Peabody Picture Vocabulary Test (PPVT): Participants were asked to choose the picture (out of four multiple-choice options) showing the meaning of a word spoken by an examiner.	CALM: 133.77 (31.68) [8, 215] NKI: N/A	CALM: 1.09 NKI: N/A	Dunn and Dunn, 2007 Wechsler, 2005
	CALM & NKI	Single Word Reading (SWR): Participants read aloud first a list of letters and then words that gradually increased in complexity. Correct responses required correctness and fluency.	CALM: 80.95 (24.35) [7, 130] NKI: 104.47 (20.28) [35, 131]	CALM: 2.36 NKI: 0	
	CALM & NKI	Spelling (Spell): Participants spelled words with increasing difficulty one at a time that were spoken by an examiner.	CALM: 21.17 (8.68) [0, 48] NKI: 33.57 (10.55) [4, 52]	CALM: 3.09 NKI: 0	
	CALM & NKI	Numerical Operations (NO): Participants answered written mathematical problems that increased in difficulty.	CALM: 14.83 (7.46) [0, 48] NKI: 27.95 (11.95) [4, 53]	CALM: 13.61 NKI: 0	
Fluid Ability (gf)	CALM & NKI	Matrix Reasoning (MR): Participants saw sequences of partial matrices and selected the response option that best completed each matrix.	CALM: 10.88 (5.44) [0, 25] NKI: 17.37 (5.19) [4, 27]	CALM: 0 NKI: 0	Wechsler, 1999 Wechsler, 2011
Working Memory (WM)	CALM & NKI	Digit Recall/Span (DR): Participants recalled sequences of single digit numbers given in audio format.	CALM: 24.22 (5.32) [7, 43] NKI: 5.97 (1.25) [3, 9]	CALM: 0.36 NKI: 24.63	Alloway, 2007 Kaufman, 1975

CALM & NKI	Backward Digit Recall/Span (BDR): Same as regular digit recall/span but in reversed order.	CALM: 9.2 (4.42) [0, 25] NKI: 4.04 (1.40) [0, 8]	CALM: 1.63 NKI: 24.63
CALM	Dot Matrix (Dot): For 2 seconds, participants were shown the location of a red dot in a sequence of 4x4 matrices and had to recollect this location by tapping the squares on a computer screen.	CALM: 17.94 (5.49) [2, 35] NKI: N/A	CALM: 0.18 NKI: N/A
CALM	Mr. X (MRX): Participants remembered spatial locations of a ball held by a cartoon man rotated in one of seven positions.	CALM: 8.94 (4.90) [0, 30] NKI: N/A	CALM: 0.91 NKI: N/A
NKI	N-Back (NB): For 500 ms participants were presented letter sequences with a further 2000 ms to respond by pressing the computer spacebar. The task consisted of three separate conditions: 0-Back– participants pressed the spacebar whenever an “X” appeared; 1-Back– participants pressed the spacebar whenever the same letter was presented twice in a row; and, lastly, 2-Back– participants pressed the spacebar each time the letter presented matched the one shown two letters beforehand.	CALM: N/A NKI: 16.32 (4.22) [0, 20]	CALM: N/A NKI: 20.47

Table 1. List and Descriptions of Cognitive Assessments used in CALM & NKI Rockland samples



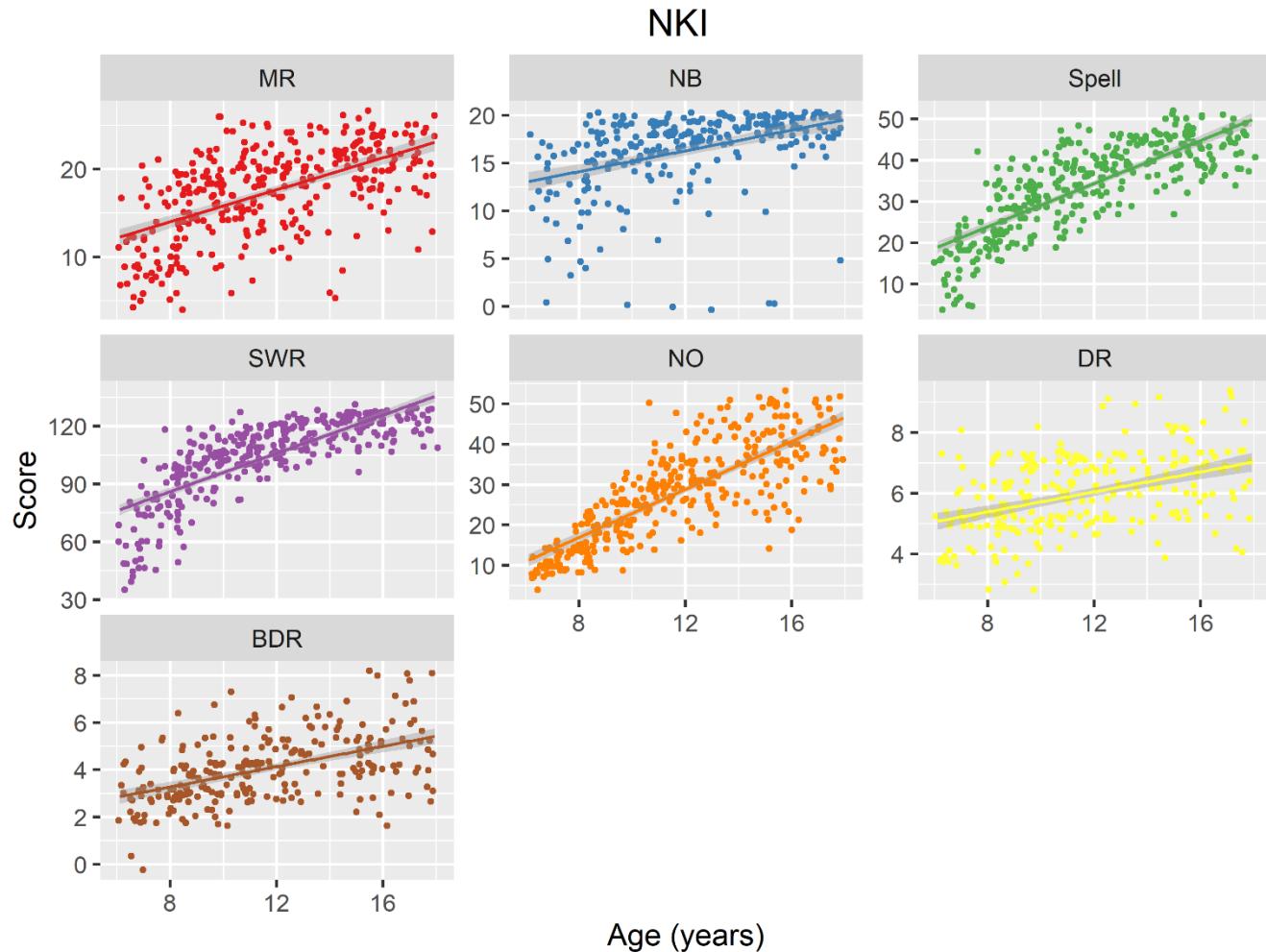


Fig. 2. Scatterplots of cognitive task scores across age for CALM and NKI Rockland samples. Lines reflect linear fit.

206 *2.1.4 MRI acquisition*

207

208 The CALM sample neuroimaging data were obtained at the MRC Cognition and
209 Brain Sciences Unit, Cambridge, UK. Scans were acquired on the Siemens 3 T Tim Trio
210 system (Siemens Healthcare, Erlangen, Germany) via 32-channel quadrature head coil.
211 Echo-planar diffusion-weighted images were used to attain diffusion scans using a set of 60
212 non-collinear directions and a weighting factor of $b=1000\text{s}^*\text{mm}^{-2}$ combined with a T2-
213 weighted ($b=0$) volume. Whole brain coverage was obtained with 60 contiguous axial slices
214 and an isometric image resolution of 2mm. Total echo time and repetition time were 90ms
215 and 8400ms, respectively.

216 For the NKI sample, participants were also scanned using a Siemens 3 T Tim Trio
217 system. All T1-weighted images were attained via magnetization-prepared rapid gradient
218 echo (MPRAGE) sequence with 1mm isotropic resolution. An isotropic set of gradients using

219 137 directions with a weighting factor of $b=1000\text{s}^*\text{mm}^{-2}$ and an isotropic resolution of 2mm
220 were used to acquire diffusion scans. For further details regarding scan sequences, see
221 http://fcon_1000.projects.nitrc.org/indi/enhanced/mri_protocol.html.

222

223 *2.1.5 White matter connectome construction*

224

225 Note that part of the following pipeline is identical to that described in Bathelt et al.,
226 (in press). Diffusion-weighted images were pre-processed to create a brain mask based on
227 the b0-weighted image (FSL BET; Smith, 2002) and to correct for movement and eddy
228 current-induced distortions (eddy; Graham et al., 2016). Subsequently, the diffusion tensor
229 model was fitted and fractional anisotropy (FA) maps were calculated (dtifit). Images with a
230 between-image displacement greater than 3mm as indicated by FSL eddy were excluded
231 from further analysis. All steps were carried out with FSL v5.0.9 and were implemented in a
232 pipeline using NiPyPe v0.13.0 (Gorgolewski et al., 2011). To extract FA values for major
233 white matter tracts, FA images were registered to the FMRIB58 FA template in MNI space
234 using a sequence of rigid, affine, and symmetric diffeomorphic image registration (SyN) as
235 implemented in ANTS v1.9 (Avants et al., 2008). Visual inspection indicated good image
236 registration for all participants. Subsequently, binary masks from a probabilistic white matter
237 atlas (threshold at >50% probability) in the same space were applied to extract FA values for
238 white matter tracts (see below).

239 Participant movement, particularly in developmental samples, can significantly affect
240 the quality, and, hence, statistical analyses of MRI data. Therefore, we undertook several
241 procedures to ensure adequate MRI data quality and minimize potential biases due to
242 subject movement. First, for the CALM sample, children were trained to lie still inside a
243 realistic mock scanner prior to their actual scans. Secondly, for both samples, all T1-
244 weighted images and FA maps were visually examined by a qualified researcher to remove
245 low quality scans. Lastly, quality of the diffusion-weighted data were evaluated in both
246 samples by calculating the framewise displacement between subsequent volumes in the
247 sequence. Only data with a maximum between-volume displacement below 3mm were
248 included in the analyses. All steps were carried out with FMRIB Software Library v5.0.9 and
249 implemented in the pipeline using NiPyPe v0.13.0 (see
250 <https://nipype.readthedocs.io/en/latest/>).

251

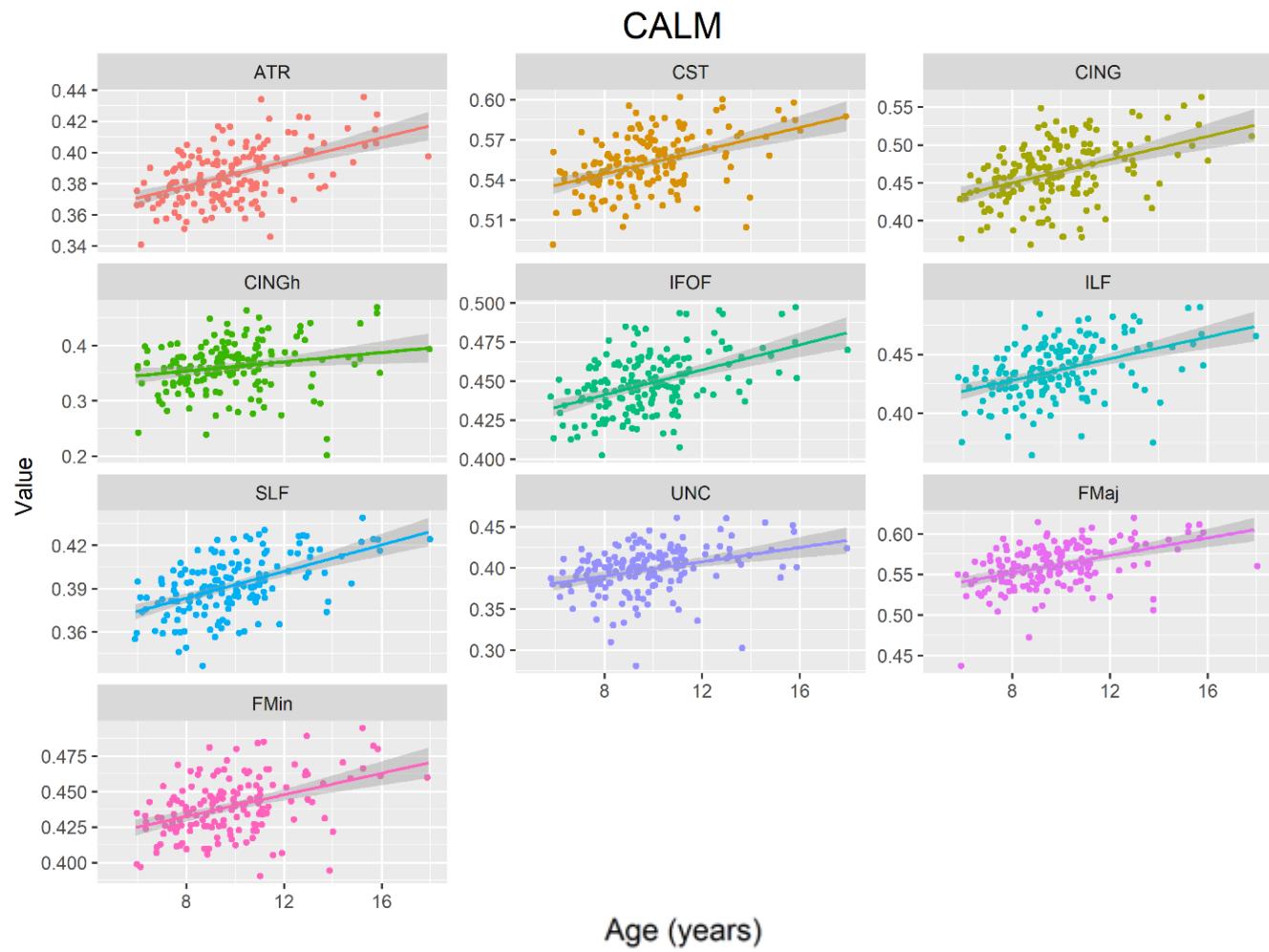
252 *2.1.6 Neural measures: white matter and fractional anisotropy*

253

254 To approximate white matter contributions to fluid and crystallized ability, we
255 analyzed fractional anisotropy (FA; see Wandell, 2016). We based our choice of FA on

256 previous studies of white matter in developmental samples (de Mooij et al., 2018; Kievit et
257 al., 2016). We used FA as a general summary metric of white matter microstructure as it
258 cannot directly discern between specific cellular components (e.g. axonal diameter, myelin
259 density, water fraction). Mean FA was computed for 10 bilateral tracts as defined by the
260 Johns Hopkins University DTI-based white matter tractography atlas (see Fig. 1 of Hua et
261 al., 2008): forceps minor (FMin), forceps major (FMaj), anterior thalamic radiations (ATR),
262 cingulate gyrus (CING), superior longitudinal fasciculus (SLF), inferior longitudinal fasciculus
263 (ILF), corticospinal tract (CST), uncinate fasciculus (UNC), cingulum [hippocampus]
264 (CINGh), and inferior fronto-occipital fasciculus (IFOF). Fig. 3 shows the cross-sectional
265 trends of FA across the age range.

266



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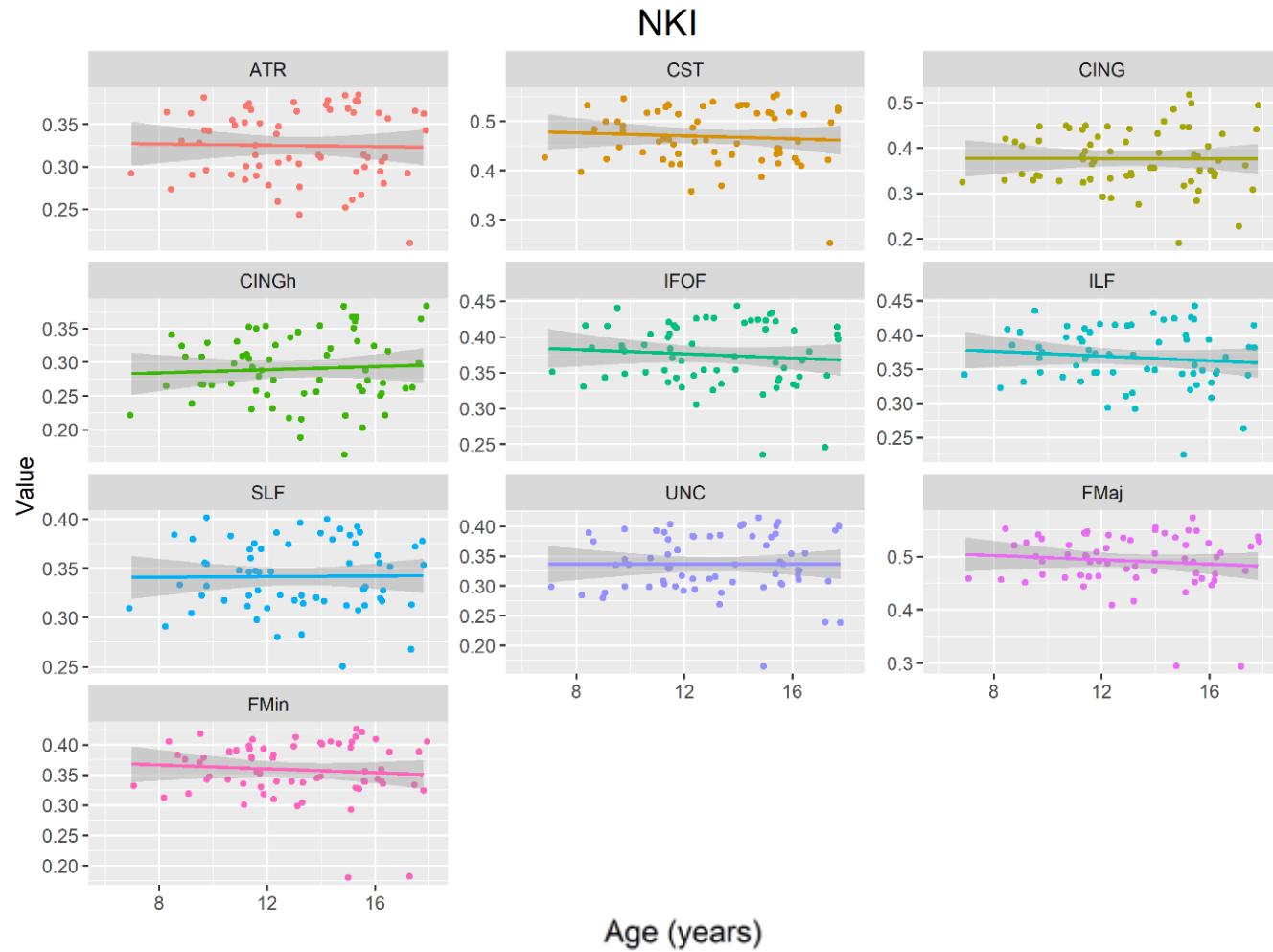


Fig. 3. Scatterplots of FA values for all white matter tracts across age for CALM and NKI Rockland samples. Lines reflect linear fit. Note that the age trends are more pronounced in CALM than in the NKI sample, possibly due to lower sample size in NKI (N=65).

268

269 3. Results

270

271 3.1 Covariance among cognitive abilities cannot be captured by a single-factor

272

273 In accordance with our [preregistered analysis plan](#), we first describe model fit for the
274 measurement models of the cognitive data only. First, we tested hypothesis 1: that gc and gf
275 are separable constructs in childhood and adolescence. More specifically, we tested the
276 hypothesis that the covariance among scores on cognitive tests would be better captured by
277 a two-factor (gc-gf) model than a single-factor (e.g. g) model. In support of this prediction,
278 the single-factor model fit the data poorly: $\chi^2 (27) = 317.695$, $p < .001$, RMSEA=.146 [.132
279 .161], CFI=.908, SRMR=.040, Yuan-Bentler scaling factor=1.090, suggesting that cognitive
280 performance was not well represented by a single-factor. The two-factor (gc-gf) model also
281 displayed poor model fit ($\chi^2 (24) = 196.348$, $p < .001$, RMSEA=.119 [.104 .135], CFI=.946,

282 SRMR=.046, Yuan-Bentler scaling factor= 1.087), although it fit significantly better
283 ($\chi^2\Delta=119.41$, $df\Delta=3$, $AIC\Delta=127$, $p<0.001$) than the single-factor model.

284 To investigate the source of poor fit, we examined modification indices (Schermelleh-
285 Engel et al., 2003), which quantify the expected improvement in model fit if a parameter is
286 freed. Modification indices suggested that the Peabody Picture Vocabulary Test had a very
287 strong cross-loading onto the fluid intelligence latent factor. The Peabody Picture Vocabulary
288 Test (PPVT), often considered a crystallized measure in adult populations, asks participants
289 to choose the picture (out of four multiple-choice options) corresponding to the meaning of
290 the word spoken by an examiner. Including a cross-loading between gf and the PPVT
291 drastically improved goodness of fit ($\chi^2\Delta= 67.52$, $df\Delta=1$, $AIC\Delta=100$, $p<0.001$) to adequate
292 ($\chi^2 (23) =104.533$, $p<.001$, $RMSEA=.083$ [.067 .099], $CFI=.975$, $SRMR=.025$, Yuan-Bentler
293 scaling factor= 1.069). A likely explanation of this result is that such tasks may draw
294 considerably more on executive, gf-like abilities in younger, lower ability samples. For a
295 more thorough investigation of the loading of PPVT across development, see Supplementary
296 Material. Notably, fitting the PPVT as a *solely* fluid task (i.e. removing it as a measurement of
297 gc entirely) did not significantly decrease model fit ($\chi^2\Delta= 2.058$, $df\Delta=1$, $AIC\Delta=1$, $p=0.152$).
298 Therefore, we decided to proceed with the more parsimonious PPVT gf-only model ($\chi^2 (24)$
299 $=106.382$, $p<.001$, $RMSEA=.082$ [.066 .098], $CFI=.972$, $SRMR=.025$, Yuan-Bentler scaling
300 factor= 1.073). We note that although this is a data-driven modification, we believe it would
301 likely generalize to samples with similarly low ages and abilities.

302 Next, we examined whether the single or two-factor model fit best in the NKI sample.
303 The single-factor model fit the data adequately ($\chi^2 (14) =41.329$, $p<.001$, $RMSEA=.075$ [.049
304 .102], $CFI=.983$, $SRMR=.029$, Yuan-Bentler scaling factor=.965). Moreover, all loadings
305 between the cognitive tasks and g were significant ($p<.05$) and high (standardized
306 loadings $\geq .5$). However, as was the case in the CALM sample, the two-factor model showed
307 considerably better fit ($\chi^2 (12) =19.732$, $p=.072$, $RMSEA=.043$ [.000 .075], $CFI=.995$,
308 $SRMR=.018$, Yuan-Bentler scaling factor=.956) compared to the single-factor model
309 ($\chi^2\Delta=20.661$, $df\Delta=2$, $AIC\Delta=17$, $p<0.001$). It should be noted that, given the differences in
310 tasks measured between the samples, gf and working memory were assumed to be
311 measurements of the same latent factor, rather than separable factors. A similar competing
312 model where gf and working memory were modeled as separate constructs with working
313 memory loaded onto gf, similarly to the best-fitting model for the CALM sample (see Fig. 4),
314 showed comparable model fit and converging conclusions with further analyses. Overall,
315 these findings suggested, that for both the NKI and CALM samples, a two-factor model with
316 separate gc and gf factors provided a better account of individual differences in intelligence
317 than a single-factor model.

318

319 *3.2 Evidence of age differentiation between crystallized and fluid ability*

320

321 We investigated the relationship between gc and gf in development to see whether
322 we could observe evidence for age differentiation as predicted by hypothesis 2. Age
323 differentiation (e.g. Hülür et al., 2011) would predict decreasing covariance between gc and
324 gf from childhood to adolescence. We fit a multigroup confirmatory factor analysis to assess
325 fit on our younger (N=279) and older (N=272) participant cohorts. The model had acceptable
326 fit (χ^2 (48) =142.214, $p<.001$, RMSEA=.085 [.069 .102], CFI= .960, SRMR=.037, Yuan-
327 Bentler scaling factor= 1.019). However, a likelihood ratio test, showed that model fit did not
328 decrease significantly when imposing equal covariance between gc and gf in the younger
329 and older participant subgroups ($\chi^2\Delta=0.323$, $df\Delta=1$ $AIC\Delta=2$, $p=0.57$). This suggested no
330 evidence for age differentiation in the CALM sample. However, the lack of association could
331 be due to limitations of using median splits to investigate age differences when independent
332 (or latent in our case) variables are correlated (Iacobucci et al., 2015). For instance, if the
333 age range of differences in behavioral associations between gc and gf lies elsewhere, the
334 median split may not be sensitive enough to detect it. To test this explicitly, we next fit SEM
335 trees (Brandmaier et al., 2013) to the cognitive data.

336 We estimated SEM trees in the CALM sample by specifying the cognitive model with
337 age as a continuous covariate. We observed a SEM tree split at age 9.12, yielding two
338 groups (younger participants = 290, older participants = 261). This split was accompanied by
339 a decrease in the covariance between gc and gf, providing support for age differentiation
340 using a more exploratory approach to determine the optimal age split (SEM tree: 9.12 versus
341 median split: 8.91).

342 Next, as in the CALM cohort, we fit a multigroup model with younger (N=169) and
343 older (N=168) age groups in the NKI sample, which produced good fit (χ^2 (24) =33.736,
344 $p=.089$, RMSEA=.047 [.000 .081], CFI= .991, SRMR=.035, Yuan-Bentler scaling
345 factor=.916). In contrast to CALM, imposing equality constraints on the covariance between
346 gc and gf across age groups revealed a lower gc-gf correlation for the older (.811) compared
347 to the younger participants cohort (1.008). This revealed significant difference in model fit
348 compared to the freely-estimated model ($\chi^2\Delta=61.244$, $df\Delta=1$ $AIC\Delta=46$, $p<0.001$). This
349 suggested evidence for age differentiation in the NKI sample using multigroup models.

350 In contrast to the multigroup model outcome, the NKI SEM tree model under identical
351 specifications as in CALM failed to produce an age split. A possible explanation is that to
352 penalize for multiple testing we relied on Bonferroni-corrected alpha thresholds for the SEM
353 tree. If, as seems to be the case here, the true split lies (almost) exactly on the median split,
354 then the SEM tree will have slightly less power than conventional multigroup models. These
355 differences between analyses methods suggested that the age differentiation observed here

356 is likely modest in size. Taken together, we interpret our findings as evidence for a small,
357 age-specific but significant decrease in gc-gf covariance in both cohorts, which is compatible
358 with age differentiation such that, for younger participants, gc and gf factors are almost
359 indistinguishable, whereas for older participants a clearer separation emerges.

360

361 *3.3 Violation of metric invariance suggests differences in relationships among*
362 *cognitive abilities in childhood and adolescence*

363

364 Finally, we more closely examined age-related differences in cognitive architecture
365 (e.g. factor loadings) by examining metric invariance (Putnick and Bornstein, 2016). Testing
366 this in the CALM sample as a two-group model by imposing equality constraints on the factor
367 loadings (fully constrained) showed that the freely-estimated model (no factor loading
368 constraints) outperformed the fully-constrained model ($\chi^2\Delta=107.05$, $df\Delta=7$, $AIC\Delta=82$,
369 $p<0.001$), indicating that metric invariance was violated. This violation of metric invariance
370 suggested that the relationship between the cognitive tests and latent variables was different
371 in the two age groups. Closer inspection suggested that the differences in loadings were not
372 uniform, but rather showed a more complex pattern of age-related differences (see Table 2
373 for more details). Some of the most pronounced differences include an increase of the
374 loading of matrix reasoning onto gf as well as increased loading of digit recall and dot matrix
375 onto working memory across age groups.

376 Similarly, in the NKI cohort, the freely-estimated model outperformed the constrained
377 model ($\chi^2\Delta=41.111$, $df\Delta=5$, $AIC\Delta=33$, $p<0.001$), indicating that metric invariance was again
378 violated as in CALM. This suggests that the relationship between the cognitive tests and the
379 latent factors differed across age groups. The pattern of factor loadings differed in some
380 respects from CALM. For example, the loading of the N-back task onto gf showed the largest
381 difference across age groups in the NKI sample. However, as CALM did not include the N-
382 back task, we cannot directly interpret this as a difference between the cohorts. For detailed
383 comparisons among factor loadings between age groups in both samples, refer to Table 2.
384 The overall pattern in both samples suggested small and varied differences in the
385 relationship between the latent factors and observed scores. A plausible explanation is that
386 the same task draws on a different balance of skills as children differ in age and ability. Our
387 findings concerning the latent factors should be interpreted in this light as it seems likely that
388 in addition to age differentiation (and possibly dedifferentiation) effects, the nature of the
389 factors also differed slightly across the age range studied here.

390

Sample	Relationship	Younger Participants	Older Participants
CALM	gc ↔gf	.89	.93
	gf →WM	.96	.90
	gf →MR	.59	.74
	gf →PPVT	.75	.76
	WM →DR	.56	.68
	WM →BDR	.76	.79
	WM →Dot	.58	.67
	WM →MRX	.59	.56
	gc → gcV	.89	.79
	gc →NO	.87	.87
	gcV →SWR	.94	.91
	gcV →Spell	.87	.91
	gc ↔gfWM	1	.81
	gc → gcV	.96	.87
NKI	gfWM →MR	.69	.60
	gfWM →DR	.38	.54
	gfWM →BDR	.50	.53
	gfWM →NB	.55	.35
	gc →NO	.90	.76
	gcV →SWR	.93	.89
	gcV →Spell	.97	.88

Table 2. Standardized Path Estimates for Cognitive Assessments in CALM & NKI Rockland samples. Note that age groups were determined according to the median split (CALM: 8.91 years, NKI: 11.38 years)

391

392 *3.4 The neural architecture of gc and gf indicates unique contributions of multiple*
 393 *white matter tracts to cognitive ability*

394

395 We next focused on the white matter regression coefficients to inspect the neural
 396 underpinnings of gc and gf. In line with hypothesis 3, we wanted to explore whether
 397 individual white matter tracts made independent contributions to gc and gf. First, we
 398 examined whether a single-factor model could account for covariance in white matter
 399 microstructure across our ten tracts. If so, then scores on such a latent factor would
 400 represent a parsimonious summary for neural integrity. However, this model showed poor fit
 401 (χ^2 (35) =124.810, $p<.001$, RMSEA=.132 [.107 .157], CFI= .938, SRMR=.039, Yuan-Bentler
 402 scaling factor=1.114), suggesting separate influences from white matter regions in
 403 supporting cognitive abilities. To examine whether the white matter tracts showed specific
 404 and complementary associations with cognitive performance, we fit a MIMIC model. Doing
 405 so, we observed that 5 out of the 10 tracts showed significant relations with gc and/or gf (Fig.

406 4). Specifically, the anterior thalamic radiations, forceps major, and forceps minor had
407 moderate to strong associations with gc with similar relations seen for gf for the superior
408 longitudinal fasciculus, forceps major, and the cingulate gyrus. Interestingly, the forceps
409 minor exhibited a negative association with gf. This could be due to modeling several highly
410 correlated paths simultaneously since this relationship was not found when only the forceps
411 minor was modeled onto gc (standardized estimate=.426) and gf (standardized
412 estimate=.386, see Tu et al., 2008). Together, individual differences in white matter
413 microstructure explained 32.9% in crystallized and 33.6 % in fluid ability.

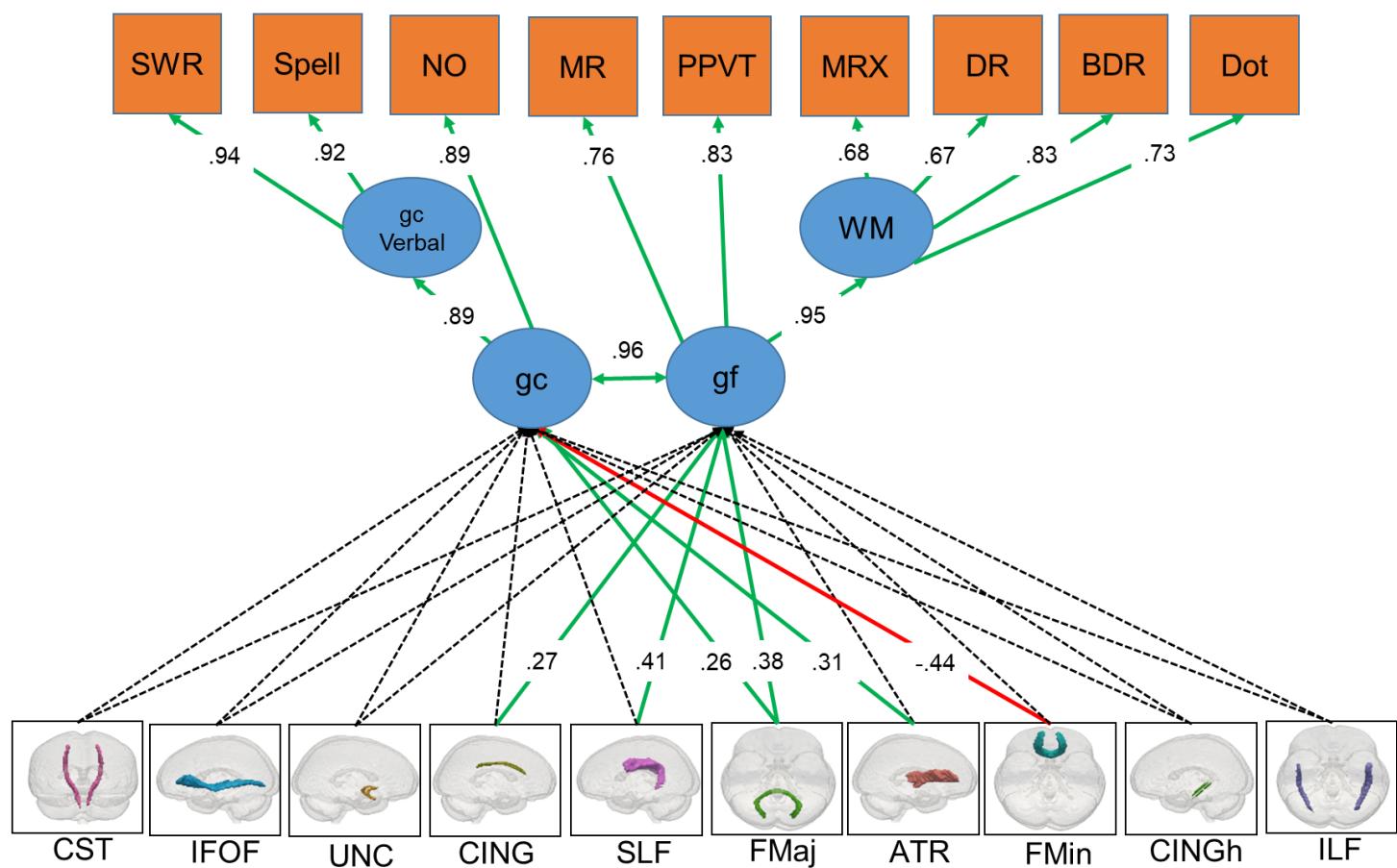
414 As in the CALM sample, the single-factor white matter model produced poor fit (χ^2
415 (35) =131.637, $p<.001$, RMSEA=.201 [.165 .238], CFI=.924, SRMR=.023, Yuan-Bentler
416 scaling factor=.950) in the NKI sample. Therefore, we fit a multi-tract MIMIC model. The
417 superior longitudinal fasciculus emerged as the only tract to significantly load onto gc or gf
418 (Fig. 4). This result was likely due to lower power associated with a small subset of
419 individuals with white matter data (N=65, see Discussion for further investigation). In NKI,
420 the same set of tracts explained 29.7% and 26.7% of the variance in gc and gf, respectively,
421 yielding similar joint effect sizes as in the CALM sample. Together, these findings
422 demonstrated generally similar associations between white matter microstructure and
423 cognitive abilities in the CALM and NKI samples. Therefore, it seems to be the case that, in
424 both typically and atypically (struggling learners) developing children and adolescents,
425 individual white matter tracts make distinct contributions to crystallized and fluid ability.

426

CALM

Model fit: $\chi^2(94) = 196.98, p < .001$; RMSEA = .045 [.036 .053]; CFI = .971; SRMR = .028

→ non-significant
 → p<.05 positive
 → p<.05 negative



427

NKI

Model fit: $\chi^2(62) = 83.42$, $p < .05$; RMSEA = .032 [.009 .048]; CFI = .987; SRMR = .107

→ non-significant
 → p<.05 positive
 → p<.05 negative

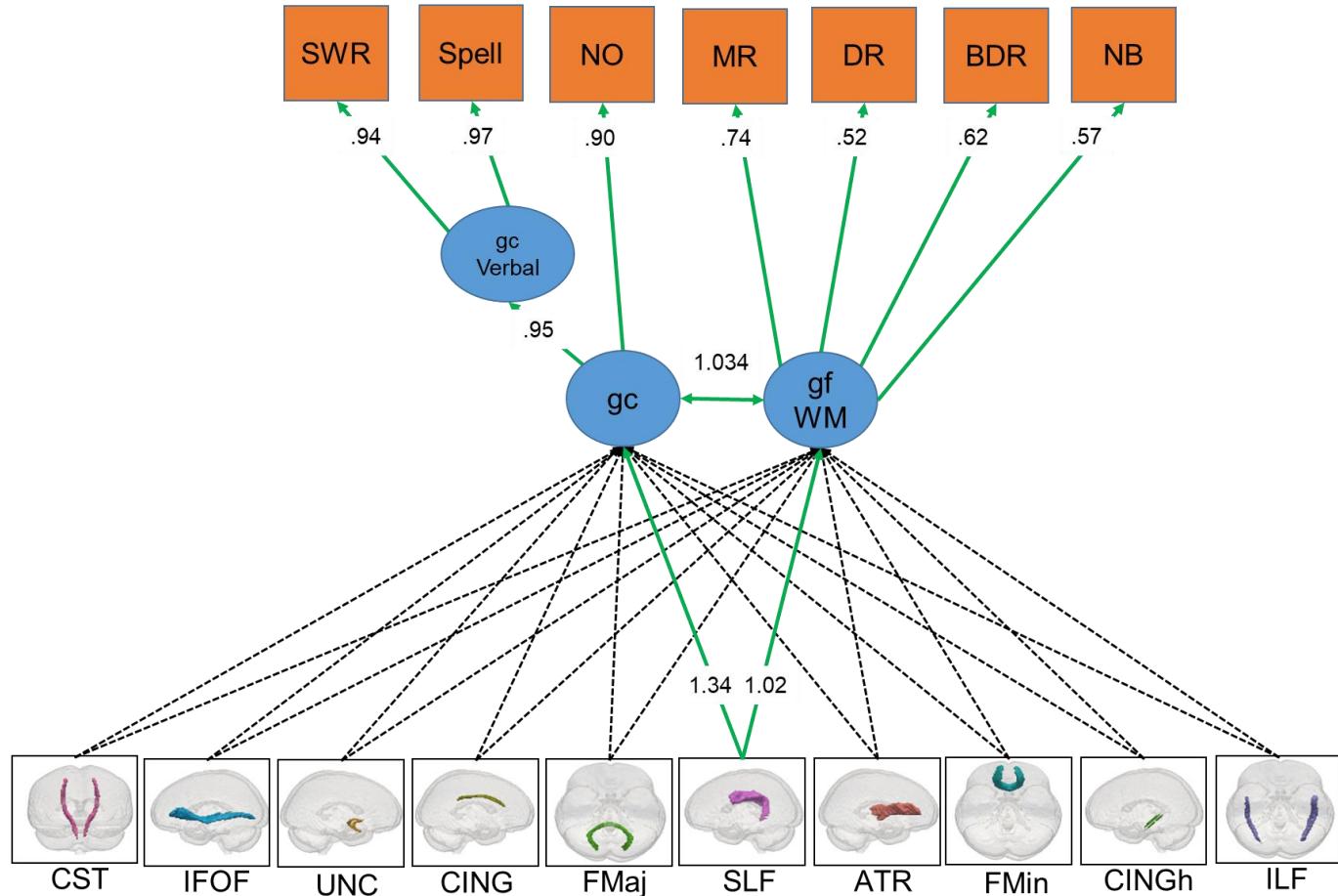


Fig. 4. MIMIC models displaying standardized parameter estimates and regression coefficients for all cognitive measures and white matter tracts for complete CALM and NKI Rockland samples. Note that the greater than 1 standardized factor loadings in NKI may occur in the presence of highly-correlated factors (Jöreskog, 1999)

428 3.5 *Support for a neurocognitive account of the age differentiation-dedifferentiation*
 429 *hypothesis*

430

431 Lastly, to address our fourth and final preregistered hypothesis, we examined
 432 whether brain-behavior associations differed across the developmental age range. We
 433 hypothesized that the relationship between the white matter tracts and cognitive abilities
 434 would decrease across the age range, in support of the differentiation hypothesis. Using a
 435 multigroup model, we compared the strength of brain-behavior relationships between
 436 younger and older participants to test whether white matter contributions to gc and gf

437 differed in development. Contrary to our prediction, we observed that, in the CALM sample,
438 a freely estimated model, where the brain-behavior relationships were allowed to vary across
439 age groups, did not outperform the constrained model ($\chi^2 \Delta= 12.16$, $df\Delta=10$, $AIC\Delta=9$,
440 $p=0.27$). This suggested that the contributions of white matter tracts did not vary significantly
441 between age groups when examined using multigroup models.

442 As before, we estimated a SEM tree model. In contrast to the multigroup model, we
443 observed that multiple white matter tracts *did* differ in their associations with gc and/or gf.
444 These differences manifested in different ways for gc and gf. For example, the correlations
445 between the cingulum, superior longitudinal fasciculus, and forceps major and gf decreased
446 with increasing age, in line with age differentiation. On the other hand, the forceps major,
447 forceps minor and anterior thalamic radiations demonstrated a more complicated pattern
448 with each tract displaying two age splits. For the first split (around age 8), the regression
449 strength decreased before spiking again around age 11 (Table 3, also see Fuhrmann et al.,
450 2019). Given that all first splits showed a decrease between white matter and cognition, and
451 all second splits revealed an increase compared to the first, this suggests a non-monotonic
452 pattern of brain-behavior reorganization that cannot be fully captured by age differentiation
453 or dedifferentiation (Hartung et al., 2018) but may be in line with theories such as Interactive
454 Specialization (Johnson, 2011), which provides a range of mechanisms which may induce
455 age-varying brain-behavior strengths.

456 Lastly, we performed the same multigroup analysis for the NKI MIMIC model, but it
457 failed to converge or produce an age split, likely due to sparsity of the neural data (N=65).
458 Therefore, this analysis could not be used to replicate the cutoff age used for multigroup
459 analyses (11.38 years) based on the median split. Further inspection of the only significantly
460 associated tract, the superior longitudinal fasciculus, revealed the same trend for gc and gf
461 with decreased correlations with increasing age (Table 3). Overall, our findings suggest the
462 need for a neurocognitive account of age differentiation-dedifferentiation from childhood into
463 adolescence.

464

	<i>Relationship</i>	<i>Estimate Before Split</i>	<i>Age of Split 1</i>	<i>Estimate After Split</i>	<i>Age of Split 2</i>	<i>Estimate After Split</i>
CALM	gc ↔gf	.64	9.12	.59	NS	NS
	gf→CING	.29	7.38	.18	NS	NS
	gf→SLF	.38	7.38	.29	NS	NS
	gf→FMaj	.38	7.38	.26	NS	NS
	gc→FMaj	.24	8.29	.04	10.79	.42
	gc→ATR	.30	7.62	.13	10.79	.37
	gc→FMin	-.34	7.62	-.52	10.79	-.25

NKI	gc↔gfWM	.96	NS	NS	NS	NS
	gf→SLF	.35	13.16	.21	NS	NS
	gc→SLF	.91	9.85	.69	NS	NS

Table 3. SEM tree Results for CALM & NKI Rockland samples. Note: values listed represent unstandardized estimates. NS= no split

465 **4. Discussion**

466

467 *4.1 Summary of findings*

468

469 In this [preregistered](#) analysis, we examined the cognitive architecture as well as the
470 white matter substrates of fluid and crystallized intelligence in children and adolescents in
471 two developmental samples (CALM and NKI). Analyses in both samples indicated that
472 individual differences in intelligence were better captured by two separate but highly
473 correlated factors (gc and gf) of cognitive ability as opposed to a single global factor (g).
474 Further analysis suggested that the covariance between these factors decreased slightly
475 from childhood to adolescence, in line with the age differentiation hypothesis of cognitive
476 abilities (Garrett, 1946; Hülür et al., 2011).

477 We observed multiple, partially independent contributions of specific tracts to
478 individual differences in gc and gf. The clearest associations were observed for the anterior
479 thalamic radiations, cingulum, forceps major, forceps minor, and superior longitudinal
480 fasciculus, all of which have been implicated to play a role in cognitive functioning in
481 childhood and adolescence (Krogsrud et al., 2018; Navas-Sánchez et al., 2014; Peters et al.,
482 2014; Tamnes et al., 2010; Urger et al., 2015; Vollmer et al., 2017). However, except for the
483 superior longitudinal fasciculus, these tracts were not significant in NKI Rockland sample. A
484 possible explanation for this is the difference in imaging sample size between the cohorts
485 (N=165 in the CALM sample versus N=65 in the NKI Rockland sample). This difference
486 implies sizeable differences in power (73.4% in CALM versus 36.2% in NKI, assuming a
487 standardized effect size of 0.2) to identify weaker individual pathways.

488 The most consistent association, observed in both samples, was between the
489 superior longitudinal fasciculus, a region known to be important for language and cognition,
490 which significantly contributed to cognitive ability in both CALM (gf only) and NKI (gc and gf).
491 The superior longitudinal fasciculus is a long myelinated bidirectional association fiber
492 pathway that runs from anterior to posterior cortical regions and through the major lobes of
493 each hemisphere (Kamali et al., 2014), and has been associated with memory, attention,
494 language, and executive function in childhood and adolescence in both healthy and atypical
495 populations (Frye et al., 2010; Urger et al., 2015). Therefore, given its widespread links

496 throughout the brain, which include temporal and fronto-parietal regions, it is no surprise that
497 it was found to be significantly related to both gc and gf in our samples.

498 Together, these results are in line with previous research relating fractional
499 anisotropy (FA) and cognitive ability. For instance, Peters et al., 2014 found that age-related
500 differences in cingulum FA mediated differences in executive functioning. Moreover, white
501 matter changes in the forceps major have been linked to higher performance on working
502 memory tasks (Krogsrud et al., 2018). The remaining tracts (superior longitudinal fasciculus
503 and anterior thalamic radiations) have also been positively correlated with verbal and non-
504 verbal cognitive performance in childhood and adolescence (Tamnes et al., 2010; Urger et
505 al., 2015). We also observed more surprising negative pathways, such as between gc and
506 the forceps minor in the CALM sample. However, closer inspection showed that the simple
507 association between forceps minor and gc was *positive*, suggesting the negative pathway is
508 likely the consequence of the simultaneous inclusion of collinear predictors (see Tu et al.,
509 2008).

510 Finally, using SEM trees (Brandmaier et al., 2013), we observed that white matter
511 contributions to gc and gf differed between participants of different ages. In CALM, the
512 contributions of the cingulum, superior longitudinal fasciculus, and forceps major weakened
513 with increasing age for gf. For gc, however, the forceps major and forceps minor, and the
514 anterior thalamic radiations exhibited a more complex pattern with each tract providing
515 significantly different effects on crystallized intelligence at two distinct time points in
516 development. In NKI, the superior longitudinal fasciculus became less associated with both
517 gc and gf. Considering that decreases in white matter relations to gc and gf occurred before
518 covariance decreases found between gc and gf suggest that differences in white matter
519 development may underlie subsequent individual differences in cognition. In a related project
520 (Fuhrmann et al., 2019, Table 6) we observed age-related differences in associations
521 despite focusing on different cognitive factors (processing speed and working memory).

522 Overall, our findings align with a neurocognitive interpretation of age differentiation-
523 dedifferentiation hypothesis, which would predict that cognitive abilities and their neural
524 substrates become more differentiated (less correlated) until the onset of maturity, followed
525 by an increase (dedifferentiation) in relation to each other until late adulthood (Hartung et al.,
526 2018). However, we note that the evidence for age differentiation-dedifferentiation was not
527 always robust across analyses methods or samples, suggesting only small effect sizes.

528

529 *4.2 Limitations of the present study*

530 First and foremost, all findings here were observed in cross-sectional samples. To
531 better understand effects such as age differentiation and dedifferentiation, future studies will
532 need to model age-related changes within the same individual. The complexity and expense

533 of collecting such longitudinal data has long precluded such investigations, but new cohorts
534 such as the ABCD sample (Volkow et al., 2018) will allow us to model longitudinal changes
535 in the future. Secondly, although the majority of our findings are similar across our cohorts,
536 some differences were observed, particularly in white matter effects. This may reflect
537 statistical variability, differences in sample size and associated differences in power, or true
538 differences between samples. Moreover, the white matter differences observed could also
539 be due to the scans being obtained at different scanner sites, although this is unlikely to
540 have produced considerable differences for all raw images were processed using the same
541 pipeline, and previous work suggests that FA is quite a robust measure in multi-site
542 comparison (see Vollmar et al., 2010).

543 CALM consists of children with referrals for any difficulties related to learning,
544 attention or memory (Holmes et al., 2019). The NKI Rockland sample, in contrast, is a
545 United States population representative sample (Nooner et al., 2012). Both samples are
546 composed of large cohorts that underwent extensive phenotyping and population-specific
547 representative sampling. Therefore, we argue that our results generalize to 'typical' and
548 'atypical' samples of neurocognitive development.

549
550 *4.3 Conclusions*
551

552 The present analyses revealed that crystallized and fluid intelligence factors
553 explained a significant amount of variance in test performance in two large child and
554 adolescent samples. These results were found in both typically and atypically (struggling
555 learners) developing cohorts, demonstrating the generalized notion that cognitive ability is
556 better understood as a two-factor rather than a single-factor phenomenon in childhood and
557 adolescence. The addition of white matter microstructure indicated independent
558 contributions from specific white matter tracts known to be involved in cognitive ability.
559 Moreover, further analyses suggested that the associations between neural and behavioral
560 measures differed during development.

561 Overall, these results support a neurocognitive age differentiation-dedifferentiation
562 hypothesis of cognitive abilities whereby the relation between white matter and cognition
563 become more differentiated (less correlated) in pre-puberty and then dedifferentiate (become
564 more correlated) during early puberty. However, despite our use of novel and more sensitive
565 statistical methods (SEM trees), the samples used were cross-sectional and, therefore, are
566 not adequate to make causal claims about the neurocognitive dynamics of intelligence in
567 childhood and adolescence. Future studies should take this limitation into account when
568 designing experiments attempting to clarify such statements.

569

570 **Declarations of interest**

571 None.

573

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575

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787

788 **Supplementary Material**

789

790 **Is the Peabody Picture Vocabulary Test a measure of fluid ability?**

791

792 As a non-preregistered exploratory analysis, we more closely examined the cross-
793 loading of the Peabody Picture Vocabulary Test (PPVT). This task asks participants to select
794 the correct picture (out of four multiple-choice options) corresponding to the meaning of a
795 word spoken by an examiner (Dunn and Dunn, 2007). As discussed previously in the
796 Results section 3.1, modification indices suggested the PPVT should either be cross-loaded
797 or solely loaded onto gf. To better understand this cross-loading, we performed an
798 exploratory (i.e. not part of preregistration) analysis using SEM tree analysis. In this analysis,
799 we allowed the PPVT to load on both gc and gf, and examined whether using age as a
800 covariate yielded a developmental period where the associations between the latent factors
801 and the PPVT task differed. This generated an age split for gf at around age 9.5 whereby the
802 loading of the PPVT decreased (from 1 to .87, unstandardized estimate).

803 Conversely, for gc the loading remained the same (.12, unstandardized estimate).
804 This suggested the PPVT as commonly implemented behaved as a fluid, rather than a
805 crystallized, task, especially in younger participants of lower ability. Although purportedly a
806 test of crystallized knowledge, the implementation of the PPVT may very well rely on more
807 fluid, executive components including response selection and reasoning, especially in a
808 cohort of children and adolescents with comparatively low overall performance.

809 A likely explanation for this pattern is that, while PPVT draws on gc, the demanding
810 nature of the task may require more fluid, executive components in younger children,
811 especially in a cohort with comparatively low overall performance (e.g. CALM). Moreover,
812 the surprisingly strong (.83, standardized) association between gf and PPVT in the full
813 sample is similar to previous research in children (Naglieri, 1981) and adults (Bell et al.,
814 2001), although with small, typically developing samples using different statistical methods.

815

816 **References**

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