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The interrelatedness of cognitive abilities in very preterm and full-term born children at 5.5 years of age: a psychometric network analysis approach

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Background: Very preterm (VP) birth is associated with a considerable risk for cognitive impairment, putting children at a disadvantage in academic and everyday life. Despite lower cognitive ability on the group level, there are large individual differences among VP born children. Contemporary theories define intelligence as a network of reciprocally connected cognitive abilities. Therefore, intelligence was studied as a network of interrelated abilities to provide insight into interindividual differences. We described and compared the network of cognitive abilities, including strength of interrelations between and the relative importance of abilities, of VP and full-term (FT) born children and VP children with below-average and average-high intelligence at 5.5 years. **Methods:** A total of 2,253 VP children from the EPIPAGE-2 cohort and 578 FT controls who participated in the 5.5-year-follow-up were eligible for inclusion. The WPPSI-IV was used to measure verbal comprehension, visuospatial abilities, fluid reasoning, working memory, and processing speed. Psychometric network analysis was applied to analyse the data. **Results:** Cognitive abilities were densely and positively interconnected in all networks, but the strength of connections differed between networks. The cognitive network of VP children was more strongly interconnected than that of FT children. Furthermore, VP children with below average IQ had a more strongly connected network than VP children with average-high IQ. Contrary to our expectations, working memory had the least central role in all networks. **Conclusions:** In line with the ability differentiation hypothesis, children with higher levels of cognitive ability had a less interconnected and more specialised cognitive structure. Composite intelligence scores may therefore mask domain-specific deficits, particularly in children at risk for cognitive impairments (e.g., VP born children), even when general intelligence is unimpaired. In children with strongly and densely connected networks, domain-specific deficits may have a larger overall impact, resulting in lower intelligence levels. **Keywords:** Preterm birth; intelligence; cognition; psychometric network analysis.

Introduction

Meta-analyses have shown that very preterm (VP, <32 weeks' gestation) born children have on average up to 13 points lower IQ than their full-term (FT) born peers (Allotey et al., 2018; Brydges et al., 2018; Twilhaar et al., 2018). Between 20 and 40 weeks' gestation, multiple rapid and complex developmental processes occur in the brain that are highly vulnerable to disruption caused by preterm birth and associated pathogenetic factors (e.g. inflammation, hypoxia, ischemia; Volpe, 2019). This leads to injury and dysmaturation of white and grey matter (Volpe, 2019) and subsequent cognitive deficits (Anderson et al., 2017). These deficits are evident as early as preschool and persist into adulthood (Arpi et al., 2019; Eves et al., 2021; Weisglas-Kuperus et al., 2009). VP born children are therefore at a significant lifelong disadvantage in both academic and everyday life, as intelligence is associated with a variety of outcomes, including academic achievement, income, life satisfaction, and mental and physical health (Brown, Wai, & Chabris, 2021). However, there are large interindividual differences in cognitive outcomes among VP born children. Heeren et al. (2017) provided more insight in this heterogeneity in a sample of extremely preterm (EP, <28 weeks of gestation) born children, by identifying four distinct cognitive profiles that differed in severity and abilities affected. The aetiology of these differences, however, remains unclear.

For decades, researchers have tried to explain individual differences in intelligence. Cognitive tests are known to positively correlate with each other. Someone who scores high on one cognitive test tends to also score high on other cognitive tests. This phenomenon is called the *positive manifold*. Its strength varies across individuals. The *ability differentiation* hypothesis states that higher cognitive ability is associated with a weaker positive manifold. Different cognitive abilities are thus less interrelated, resulting in a more differentiated cognitive structure in which abilities are more specialised and distinctly recognisable (Breit, Brunner, & Preckel, 2020, 2021). The positive manifold has been ascribed to a single underlying general factor, *g* (Spearman, 1904).

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More recently, the existence of *g* as a psychological attribute has been questioned and alternative theories of intelligence have been proposed. According to the mutualism model, cognitive abilities reciprocally influence each other during development (van der Maas et al., 2006). Specifically, growth in a certain cognitive ability results from autonomous growth of that ability and from reciprocal influences of growth in other cognitive abilities. As a result, cognitive abilities become positively interrelated over the course of their development. However, growth is restricted by ability-specific limiting capacities. These capacities vary across individuals as a function of genetic and environmental factors, giving rise to individual differences in abilities (van der Maas et al., 2006; van der Maas, Kan, Marsman, & Stevenson, 2017). Process Overlap Theory (POT) assumes that any cognitive test requires both domain-general and domain-specific processes. Domain-general processes include primarily executive processes (e.g. goal maintenance, updating, inhibition) that are involved in a variety of tasks, whereas domain-specific processes are particularly involved in certain types of tasks (e.g. verbal, spatial, numeric). Positive correlations between tests arise because of overlapping domain-general executive processes and domain-specific processes that are involved in these tests (Kovacs & Conway, 2016). Domain-general executive processes are involved in most tests and constrain performance to various extents because of individual differences in these processes. For example, individuals with deficits in executive processes are more likely to perform poorly across test items, despite unaffected domain-specific processes (e.g. spatial reasoning) involved in some parts of the test.

In line with these contemporary theories and criticisms of *g* being merely a statistical artefact of latent factor analysis, the present study considered the structure of intelligence as a system of interrelated abilities without presuming a single underlying general factor (Schmank, Goring, Kovacs, & Conway, 2019; van der Maas et al., 2017). These contemporary theories are compatible with psychometric network analysis, which was applied in the current study as a viable alternative to factor models. Our main objective was to provide insight in the intelligence structure and increase our understanding of individual differences in VP and FT born children at 5.5 years of age. To this end, we described and compared the networks of cognitive abilities, including the strength of interrelations and the relative importance of abilities, in VP and FT born children and in VP children with lower compared to higher IQ. In line with ability differentiation, it was hypothesised that abilities were more strongly interrelated in VP than FT children and in VP children with lower compared to higher IQ. Based on the proposed central role of working memory (WM) by mutualism (van der Maas et al., 2017) and a previous network analysis of intelligence in adults (Schmank et al., 2019), WM was expected to be one of the most central abilities in the network across samples.

Methods

Subjects

EPIPAGE-2 is a prospective population-based cohort study of infants born preterm with a gestational age (GA) between 22 and 34 weeks in France (Lorthe et al., 2021). Participants were recruited between March 28 and December 31, 2011. The present study focuses on EP and VP born children (GA < 32 weeks) at 5.5 years of age, of whom 2,253 children with available follow-up data and no chromosomal and/or severe congenital abnormalities were eligible for inclusion. Infants born between 22 and 26 weeks GA were recruited during an 8-month period and those born between 27 and 32 weeks GA during a 6-month period (Lorthe et al., 2021). Detailed information about the inclusion and exclusion from birth to 5.5 years is presented in Figure 1.

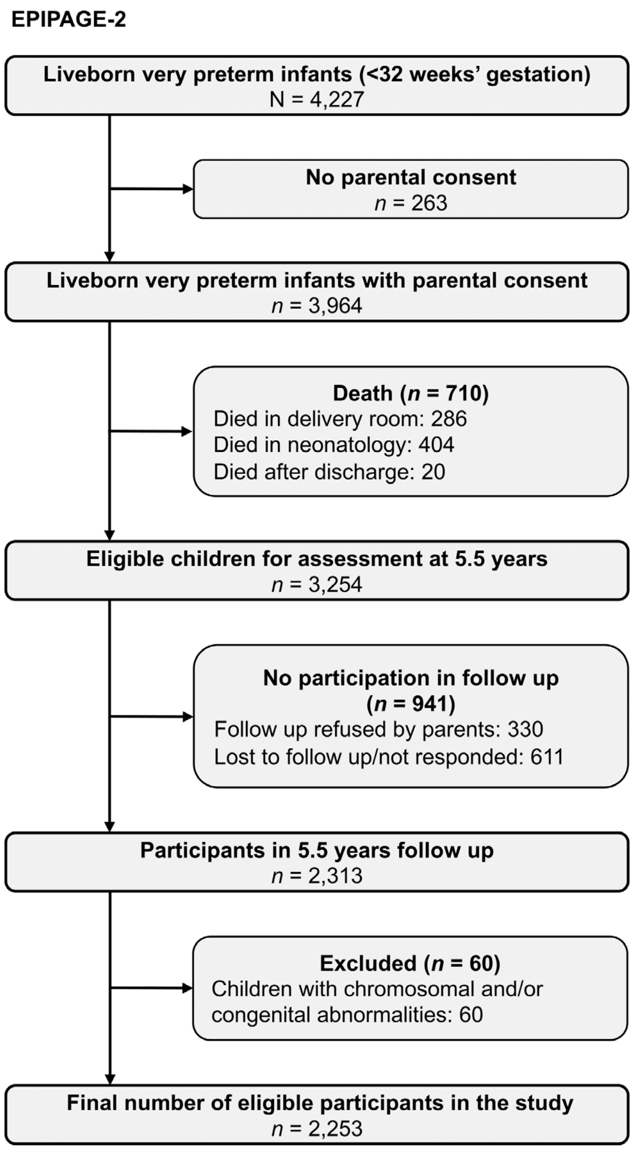

Figure 1 Flowchart for very preterm born children from birth to follow-up at 5.5 years

A total sample of 578 FT born peers, born between 37 and 40 weeks GA and with available follow-up data were included as a reference sample. FT children with chromosomal and/or severe congenital abnormalities were excluded from the analysis. The FT children were part of the larger population-based ELFE study (N = 18,040; Charles et al., 2020). For financial-organisational reasons, a subsample of 600 of these children was subjected to the same assessments as the VP children, which was a sufficient number to ensure good precision of test scores (Pierrat et al., 2021).

Cognitive assessment

The Wechsler Preschool and Primary Scale of Intelligence, Fourth Edition (WPPSI-IV) (Wechsler, 2012), for the older age group (i.e., 4:0 to 7:7) was used to assess cognitive abilities at 5.5 years of age. WPPSI-IV assesses five areas of cognitive functioning, namely verbal comprehension index (VCI), visuospatial index (VSI), fluid reasoning index (FRI), working memory index (WMI) and processing speed index (PSI). These primary indices are composite scores, each made up of two core subtests, with a mean of 100 and a standard deviation of 15. The descriptions of these subtests and the abilities they measure can be found in Table 1.

Procedure

Follow-up at 5.5 years of age was conducted between September 2016 and December 2017. Written informed consent for participation was obtained from both parents. A set of neuropsychological tests, including the WPPSI-IV, were administered by trained psychologists. The study was approved by the National Data Protection Authority (CNIL DR-2016-290), the Consultative Committee on Treatment of Information on Personal Health Data for Research Purposes (no. 16.263), and the Committee for Protection of People Participating in Biomedical Research (no. 2016-A00333-48).

Statistical analyses

Missing data evaluation. R (version 4.1.1; R Core Team, 2021) was used for data-analysis. Missing data were analysed and visualised with the R packages VIM (Kowarik & Templ, 2016), mice (Van Buuren & Groothuis-Oudshoorn, 2011), and naniar (Tierney, Cook, McBain, & Fay, 2021). Perinatal and socio-economic characteristics of the VP sample with complete WPPSI-IV data, with one or more missing WPPSI-IV subtest scores and those lost to follow-up were compared. ANOVA and independent samples t-test were used to compare the means of continuous data, and χ^2 test to compare frequencies of categorical variables. Means, SDs, percentages, t-tests, ANOVA and χ^2 were weighted by sampling weights to account for differences in recruitment duration in the VP sample (Pierrat et al., 2021).

Cognitive outcomes. Differences in mean full-scale IQs, index scores, and specific subtests between the VP and FT samples were tested with an independent samples t-test. Cohen's d was used to quantify effect sizes, with .2, .5, and .8 indicating small, medium, and large effect sizes, respectively (Cohen, 1988). Cases with missing data for all subtests were excluded from the analyses. For cases with incomplete WPPSI-IV data, missing data were handled by multiple imputation by chained equations with predictive mean matching. In total, 50 imputed datasets were generated (5 iterations each). Neonatal characteristics, parental socioeconomic status and cognitive scores were included as predictors.

To define VP subsamples with below-average and average-high intelligence levels, a cut-off point of 93 was used as described in Pierrat et al. (2021), corresponding to 1 SD below the mean of the FT sample after weights were applied to improve the sample's representativeness (Charles et al., 2020).

Psychometric network analysis. In a psychometric network, observed variables are presented as nodes, while edges and edge weights represent statistical associations and the strength of these associations between nodes, respectively (Epskamp, Borsboom, & Fried, 2018). The 10 core subtests were used as nodes. Although these subtests involve multiple abilities, we refer to them as single cognitive abilities for simplicity. Network estimation was performed using qgraph (Epskamp, Cramer, Waldorp, Schmittmann, & Borsboom, 2012) as implemented in the bootnet package (Epskamp et al., 2018). We estimated four Gaussian graphical models, where edges represent partial correlation coefficients (Epskamp, Kruis, & Marsman, 2017), using regularisation (EBICglasso) to identify cognitive networks of VP and FT born children and VP children with below-average and average-high IQ. The EBICglasso estimator was used because it works well in retrieving an overall structure that resembles a true network while depicting non-prominent edges in faded colours or setting them to zero, thus reducing the risk of spurious connections (Epskamp & Fried, 2018; Isvoranu & Epskamp, 2021). Using graphical lasso, multiple regularised networks were estimated, with the level of sparsity being dictated by the tuning parameter lambda. The best-fitting model was then chosen using the extended Bayesian information criterion (EBIC), where the hyperparameter gamma determines how conservative EBIC will be (Epskamp & Fried, 2018). Gamma was set to 0.5 according to guidelines (Epskamp & Fried, 2018; Foygel & Drton, 2010). Missing data

Table 1 Overview of included WPPSI-IV subtests and their measurement aims

Index	Subtest	Measurement aim
Verbal Comprehension (VCI)	Information	Capacity to acquire, remember, and retrieve general information
	Similarities	Ability to form verbal concepts and abstract reasoning skills
Visuospatial (VSI)	Object Assembly	Visuospatial processing, analysis and synthesis of meaningful visual information
	Block Design	Visuospatial processing, analysis, and synthesis of abstract visual information
Fluid Reasoning (FRI)	Matrix Reasoning	Fluid and inductive reasoning and the ability to classify information
	Picture Concepts	
Working Memory (WMI)	Picture Memory	Visual working memory and proactive interference control
	Zoo Locations	Visuospatial working memory and proactive interference control
Processing Speed (PSI)	Bug Search	Processing speed and visual discrimination
	Cancellation	Visual search processing speed

Adapted from Raiford & Coalson, 2014.

were handled by full information maximum likelihood estimation.

Model fit was evaluated based on RMSEA, TLI, and CFI indices, with RMSEA <.06–.08 and TLI/CFI values ≥.95 indicating good fit (Schreiber, Nora, Stage, Barlow, & King, 2006). To identify the most important nodes in the networks, strength centrality was computed using bootnet. Strength centrality corresponds to the combined strength (edge weights) of a node's connections (Opsahl, Agneessens, & Skvoretz, 2010). To quantify the degree of centrality, a strength *z*-score ≥1 *SD* above the mean was defined as strong centrality (Simpson-Kent et al., 2021). Furthermore, node predictability, which is based on the proportion of explained variance (R^2) was calculated and visualised to assess how well a certain cognitive ability is predicted from other abilities that are directly linked to it, thereby giving further insight into the relevance of its connections (Haslbeck & Waldorp, 2018).

To compare differences in global strength of connectivity, network structure, and centrality across samples, the Network Comparison Test from the NetworkComparisonTest package was used (Van Borkulo et al., 2022). Based on a simulation study by Van Borkulo et al. (2022), high power (≥0.8) can be expected when the number of nodes in the network is low (i.e., 10) and the sample size of one network is at least 500, which resembles our conditions. Bonferroni-Holm method was used to correct for multiple testing.

The accuracy and stability of estimated network models were assessed using the bootnet package. The accuracy of estimated edge weights was determined by estimating 95% non-parametric bootstrapped confidence intervals (CI). Stability of strength centrality was estimated by non-parametric case-dropping subset bootstrap to assess whether the order of nodes based on their strength remains stable when decreasing the number of cases in the sample (Epskamp et al., 2018). This was quantified by the correlation stability (CS) coefficient, which indicates the proportion of cases that can be dropped while retaining a 0.7-correlation between centrality values of the original and subset samples. Values above 0.5 indicate that the order of strength centrality can be interpreted, whereas values below 0.25 indicate that it is not interpretable (Epskamp et al., 2018).

To explore the specific role of VP birth, network analyses were repeated in IQ-matched balanced samples. Samples were matched on FSIQ with optimal pair matching, using the R package MatchIt (Ho, King, Stuart, & Imai, 2011). In addition, sensitivity analyses excluding children with cerebral palsy and/or moderate–severe neurosensory impairments were performed to evaluate the robustness of the main findings against the influence of cases at high risk for intellectual impairment or compromised test performance.

Results

Missing data evaluation

A total of 1,906 of the 2,253 VP born children participating at 5.5 years follow-up completed all WPPSI-IV subtests. The total percentage of missing data for WPPSI-IV subtests was 15%, of which 303 (13%) VP children had no data available and 44 (2%) VP children had some data available. Furthermore, 570 of the 578 FT born controls completed all WPPSI-IV subtests. For half (n = 4) of the FT children with missing data all subtests were missing. A total of 1,950 VP and 574 FT born children with available WPPSI-IV data were used in the network analysis.

Comparison of VP children with complete (n = 1,906) and incomplete WPPSI-IV data (i.e., 1 or more subtests were not completed; n = 347) as well as those lost to follow-up at 5.5 years (n = 941) is presented in Table 2. Regarding neonatal characteristics, VP children who did not participate in follow-up were born to younger mothers and the percentage of multiple birth in this group was lower compared to children who participated in follow-up. Furthermore, VP children who were lost to follow-up were more frequently born to mothers who were born outside Europe and with a lower level of education at birth compared to VP children who participated in follow-up. The percentage of parents with a low educational level at 5.5 years was higher in children who did not complete one or more WPPSI-IV subtests compared to children who completed all subtests. Additionally, a higher percentage of children with incomplete cognitive assessment had cerebral palsy and had significantly lower WPPSI-IV index scores compared to children with a complete assessment.

Cognitive outcomes

All WPPSI-IV scores were significantly lower in the VP sample (Table 3). The most affected cognitive domains were visuospatial (d = .8) and verbal (d = .8) abilities, whereas a medium effect size was observed for WM (d = .5). On the individual level, 38% of the VP born children had a below-average IQ (i.e., below 1 *SD* of the FT mean; <93), 57% had an average IQ (i.e. within 1 *SD* of the FT mean; 93–119; Pierrat et al., 2021) and 5% had an above average IQ (i.e. above 1 *SD* of the FT mean; >119). Table S1A–D shows the full correlation matrix of all groups.

Network visualisation, description, and comparison

Very preterm and full-term sample. The network models showed good fit (Table S2). The VP and FT networks (Figure 2, *left panel*) were both densely connected (edge density VP, FT = 0.93, 0.91), with many positive links between abilities from different cognitive domains. In both networks, the strongest connections were observed between subtests within the same cognitive domain. This was especially prominent for nodes relating to verbal, visuospatial and processing speed abilities (Figure 2, Figure S1). Due to wide confidence intervals, estimated edge weights of the FT sample should be interpreted with caution (Figure S1). The majority of abilities in the VP sample were strongly predicted from their connected abilities, in contrast to those in the FT sample. For instance, the degree of explained variance was highest for Similarities (R^2 = .27) and Information (R^2 = .24), which is approximately half as much as in the VP network (Table S3).

The most strongly connected abilities in the VP network (Figure 2) were Similarities (z = 1.01) and Information (z = 0.95), which measure verbal ability, followed by processing speed (e.g., BS [z = 0.94]), and visuospatial ability (e.g. BD [z = 0.92]). Strength

Table 2 Characteristics of very preterm born children with complete or incomplete WPPSI-IV data and very preterm born children not included in the analysis

	Complete WPPSI-IV (n = 1,906)	Incomplete WPPSI-IV (n = 347)	Lost to 5-year Follow-up (n = 941)	p
Neonatal characteristics				
Sex, % male	52.0	52.2	52.9	.90
Gestational age at birth (week), mean (*SD*)	28.9 (1.9)	30.0 (1.9)	29.0 (1.9)	.78
Birth weight (g), mean (*SD*)	1224.9 (344.1)	1229.5 (338.1)	1239.3 (342.8)	.58
Multiple birth, %	33.7	33.6	29.8	**.01**
Moderate/severe bronchopulmonary dysplasia, %	11.6	13.2	10.0	.25
Severe brain lesions, %	4.8	6.5	5.8	.30
Late-onset sepsis, %	21.3	20.2	18.6	.23
Necrotizing enterocolitis, %	3.4	3.6	4.0	.73
Parental characteristics				
Maternal age at delivery (years), mean (*SD*)	30.2 (5.8)	30.0 (5.6)	29.0 (6.4)	**<.001**
Maternal country of birth, %				
France	80.2	77.6	67.9	**<.001**
Other European country	2.1	3.5	3.4	
North African country	7.2	10.5	10.2	
Other African country	6.1	5.2	11.0	
Other	4.4	3.2	7.5	
Maternal educational level at birth, %				
Less than upper secondary education	46.2	59.4	67.9	**<.001**
Upper/post-secondary or short tertiary education	24.5	18.2	16.2	
Bachelor's degree or higher	29.3	22.4	15.8	
Parental educational level at 5.5 years, %				
High school or lower	36.8	51.7	NA	**<.001**
Post-secondary or short tertiary education	26.2	21.3	NA	
Higher education	37.0	27.1	NA	
Disability at 5.5 years				
Cerebral palsy, %	4.4	28.5	NA	**<.001**
Moderate/severe neurosensory problems, %	1.4	3.6	NA	.08
Cognitive score (WPPSI-IV)				
Verbal comprehension index, mean (*SD*)	99.3 (15.9)	76.9 (24.4)	NA	**<.001**
Visuospatial index, mean (*SD*)	96.9 (14.2)	74.8 (17.2)	NA	**<.001**
Fluid reasoning index, mean (*SD*)	97.9 (14.8)	81.4 (16.3)	NA	**<.001**
Working memory index, mean (*SD*)	95.1 (12.9)	80.4 (14.9)	NA	**<.001**
Processing speed index, mean (*SD*)	96.1 (14.4)	73.8 (14.5)	NA	**<.001**
Full-scale IQ, mean (*SD*)	96.2 (14.8)	69.1 (21.5)	NA	**<.001**

Means, *SD*s, percentages, *t*-tests, ANOVA and χ^2 were all weighted by sampling weights. Bold values indicate significant differences across samples (p < .05). Bronchopulmonary dysplasia: ≥28 days of >21% oxygen supply and <30% oxygen (moderate) or ≥30% oxygen and/or positive pressure (severe) at 36 weeks post-menstrual age; severe brain lesions: intraventricular haemorrhage grade 3/4, cystic periventricular leukomalacia; late-onset sepsis: positive blood culture and ≥5 days of antibiotics treatment; necrotising enterocolitis: Bell stages 2–3; parental educational level: highest level of education of both parents or one parent in single-parent households (low: high school or lower, intermediate: post-secondary or short tertiary education; high: bachelor degree or higher); cerebral palsy: Gross Motor Function Classification System level 1 or higher; moderate–severe neurosensory problems: binocular visual acuity <3.2/10 and/or uni- or bilateral hearing loss >40 dB not or partially corrected with hearing aids.

centrality varied across abilities in the VP sample, in which certain abilities had significantly higher strength than others (Figure S2). Much less differences were observed in the FT sample. WM had the lowest strength centrality. In the FT sample, the order of node strength could not be reliably interpreted because of the low CS coefficient (see Network stability paragraph). The Similarities subtest (verbal ability) showed strong centrality (i.e., $z \geq 1$ *SD* above the mean) in both the VP and FT sample.

Network comparison: The network of VP born children was more strongly interconnected than the network of FT born children (distance measure $S = 0.58$, $p < .001$). No statistically significant differences in network structure (i.e., in individual edges) were found (distance measure $M = 0.13$, $p = .19$). Statistically significant differences in strength centrality were found for Information (p = .02) and Cancellation (p = .02) between the two networks, which were less strongly connected in the FT compared to the VP network.

Very preterm sample: below-average vs. average-high IQ. The fit of both models was good (Table S2). The network of VP born children with below-average IQ (Figure 3, *top left panel*) was densely connected (edge density = 0.84), whereas the network of VP born children with average-high IQ (Figure 3, *bottom left panel*) was the least densely connected network (edge density = 0.67) of all estimated networks. Individual abilities in the latter were also the least

Table 3 Comparison of WPPSI-IV scores between VP and FT born children

WPPSI-IV scores	VP children (n = 1,950) M (SD)	FT children (n = 574) M (SD)	p	Cohen's d
Subtests				
Information scaled score	9.5 (3.0)	11.4 (2.7)	<.001	.7
Similarities scaled score	10.1 (3.3)	12.3 (2.6)	<.001	.7
Block design scaled score	9.3 (2.8)	11.6 (2.9)	<.001	.8
Object assembly scaled score	9.5 (2.9)	11.2 (2.5)	<.001	.6
Matrix reasoning scaled score	9.7 (2.8)	11.2 (2.7)	<.001	.6
Picture concepts scaled score	9.5 (3.3)	11.3 (2.8)	<.001	.6
Picture memory scaled score	9.2 (2.9)	10.4 (3.0)	<.001	.4
Zoo locations scaled score	9.1 (2.7)	10.1 (2.5)	<.001	.4
Bug search scaled score	9.1 (2.6)	10.7 (2.6)	<.001	.6
Cancellation scaled score	9.4 (3.1)	10.8 (2.6)	<.001	.5
Indices				
Verbal comprehension index	98.8 (16.4)	110.5 (13.1)	<.001	.8
Visual spatial index	96.4 (14.6)	108.0 (13.1)	<.001	.8
Fluid reasoning index	97.4 (15.1)	107.2 (13.8)	<.001	.7
Working memory index	94.8 (13.2)	101.2 (13.2)	<.001	.5
Processing speed index	95.6 (14.8)	104.5 (12.7)	<.001	.6
Full scale IQ	95.7 (15.2)	109.2 (12.5)	<.001	.9

Imputed unweighted data are presented.

strongly predicted from their connections, with the proportion of explained variance ranging from R^2 = .01 for WM (i.e., ZL) to R^2 = .13 for verbal ability (i.e. SI).

The most strongly connected abilities in the network of children with below-average IQ were processing speed (e.g., CA [z = .91]), followed by visuospatial (e.g. OA [z = 0.89]) and verbal abilities (e.g. IN [z = 0.86]). In contrast, the most strongly connected abilities in the network of VP children with average-high IQ were visuospatial ability (e.g., OA [z = 0.63]) and fluid reasoning (e.g. PC [z = 0.59]). Again, WM was least strongly connected to other abilities in both networks. The Bug Search and Cancellation subtests (processing speed) showed strong centrality in the VP sample with below-average IQ, whereas the Object Assembly subtest (visual–spatial ability) had strong centrality in the VP sample with average-high IQ. Within samples, the degree of centrality varied across abilities in children with below-average IQ, which was generally not true for children with average-high IQ (Figure S2).

Network comparison: The network of children with below-average IQ was more strongly interconnected than the network of children with average-high IQ (S = 1.32, p < .001). The test on invariant network structure was statistically significant (M = 0.20, p < .001). Specifically, the networks differed in three edges: Information-Similarities (p = .02), Matrix reasoning-Picture concepts (p = .03) and most remarkably Information-Cancellation (p < .001), which showed a positive correlation (bootstrapped edge-weight = .20; 95% CI [.14, .27]) in the group with below-average IQ but were unrelated in the group with average-high IQ. Moreover, the relative importance of all cognitive abilities, except for those measured with Block Design, was significantly higher in the sample with below-average IQ.

Network stability. Variability was observed in edge-weight accuracy (Figure S1). In the VP network, for example, IN-SI, BS-CA, and BD-OA were the most accurately estimated edges, whereas CIs of other edges were wider. Estimated edge-weights were least precise for the FT network. Therefore, the strength of edges with wide CIs should be interpreted with caution (Epskamp et al., 2018).

The stability of strength centrality was highest in the VP network (CS = 0.75), meaning that the order of node strength could be interpreted (Figure S3). Furthermore, the stability of strength was acceptable in the networks of VP children with below-average IQ (CS = 0.67) and with average-high IQ (CS = 0.52). In contrast, the order of node strength could not be reliably interpreted in the FT network, as correlations with the original sample decreased steeply in the subsamples with dropped cases (CS = 0.36).

IQ-matched samples. Optimal pair matching resulted in matched and balanced samples in terms of FSIQ of VP (n = 573, M = 108.73, SD = 11.90) and FT (n = 573, M = 109.18, SD = 12.45) born children. Despite similar FSIQs, processing speed and visuospatial ability were considerably lower in the VP compared to the FT sample (Table S4). Comparison of cognitive networks in these samples yielded no differences in network structure, strength, and centrality (Figure S4).

Sensitivity analysis. Exclusion of children with cerebral palsy and/or moderate–severe neurosensory problems (n = 140) did not alter the main results. VP (n = 1824) born children had more strongly interconnected networks than FT (n = 570)

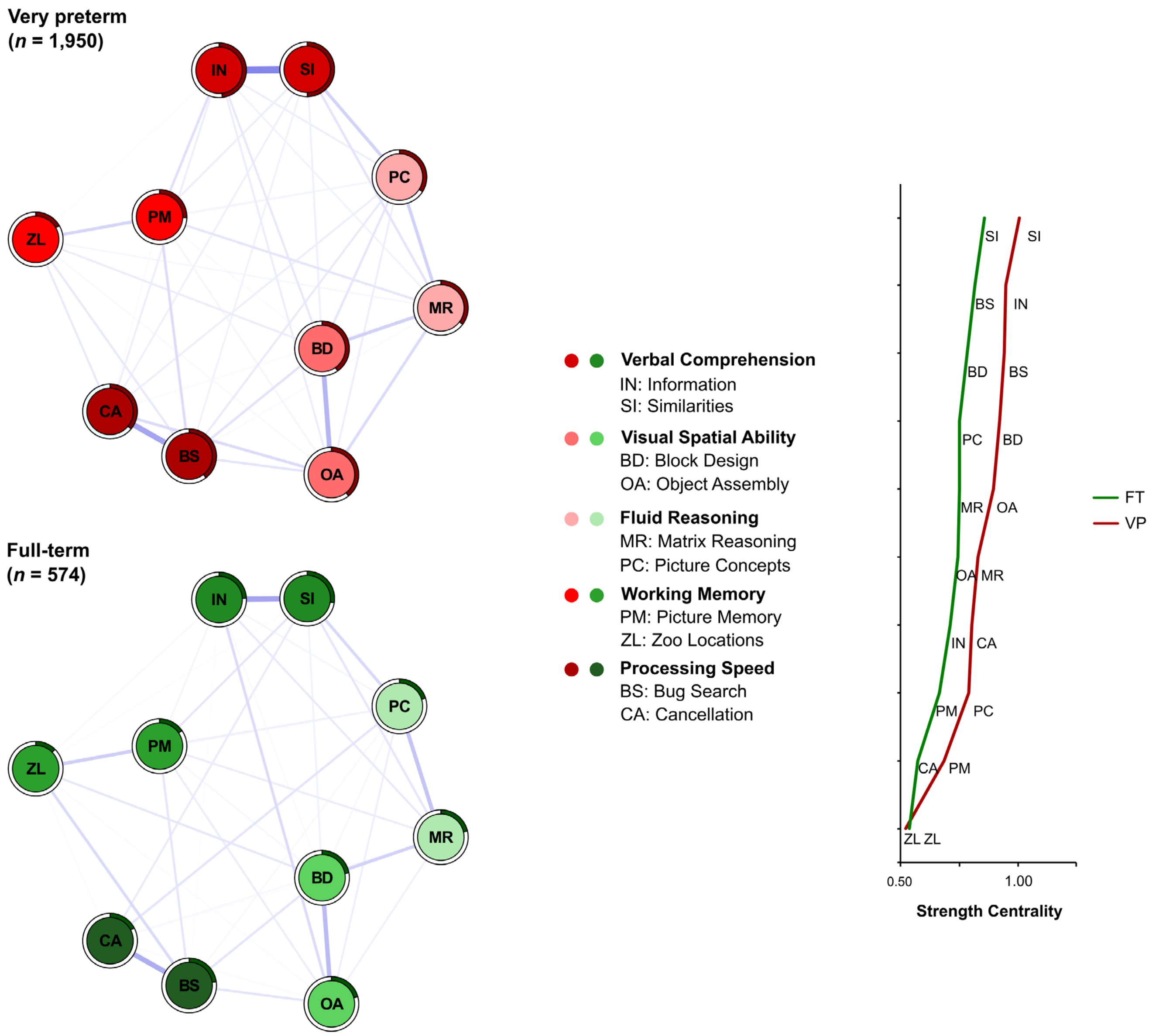

Figure 2 Network models of cognitive abilities for very preterm and full-term born children (*left panel*) and the corresponding strength centrality (*right panel*). Nodes represent WPPSI-IV subtests, where the similarly coloured nodes represent the same cognitive domain. Edges between the nodes are regularised partial correlation coefficients. Thicker edges and darker blue colour correspond to stronger positive strength. The coloured rings around the nodes represent node predictability (R^2). Strength centrality is depicted as standardised *z*-scores. FT, full-term; VP, very preterm

born children ($S = 0.50$, $p < .001$), whereas no differences in network structure were observed. Strength centrality differed only for Information ($p = .01$), which was more strongly connected to other subtests in the VP than in the FT group.

Discussion

This study is the first to provide insight into the structure of intelligence in large population-based samples of VP and FT born children at 5.5 years of age. In both samples, cognitive abilities formed a strongly interrelated network at this age. Nevertheless, important differences in the strength of connectivity in the networks were observed between groups. Cognitive abilities were more strongly interrelated in VP compared to FT born children. Within the VP group, the cognitive network of children with below-average intelligence levels was more strongly interrelated than that of children with average to high intelligence levels. WM had the least central role in all networks, whereas processing speed, visuospatial and verbal abilities were most interconnected.

The presence of exclusively positive edges between abilities in our four network models of intelligence reflect the positive manifold. Although associations between some abilities were weak or non-existent, simulation studies of the mutualism model show that even when edge-weights are sparse, including zero or weak edges, they can still give rise to a positive manifold (van der Maas et al., 2006).

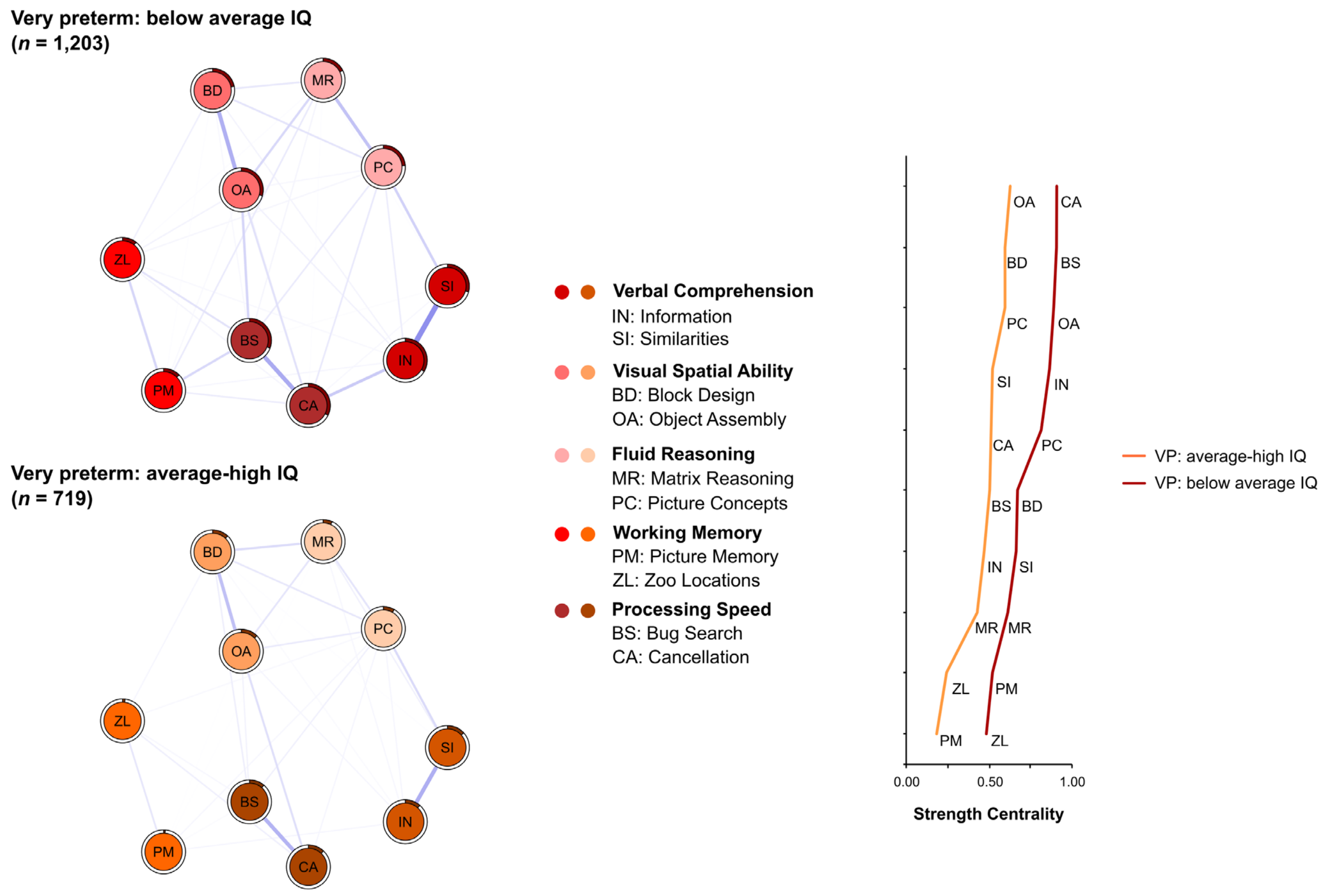

Figure 3 Network models of cognitive abilities for very preterm born children with below-average and average-high IQ (*left panel*) and the corresponding strength centrality (*right panel*). Nodes represent WPPSI-IV subtests, with similarly coloured nodes representing the same cognitive domain. Edges between the nodes are regularised partial correlation coefficients. Thicker edges and darker blue colour correspond to higher positive strength. The coloured rings around the nodes represent node predictability (R^2). Strength centrality is depicted as standardised *z*-scores. IQ, intelligence quotient, VP, very preterm

Network models of intelligence, including ours, have been found to provide a good fit to intelligence data (Kan, van der Maas, & Levine, 2019; Schmank et al., 2019). Overall, these results support modelling intelligence as a network in line with contemporary theories of intelligence. From a mutualism perspective, positive interrelations are seen as causal interactions between abilities that were measured by different cognitive tasks. Applying this to the cognitive networks in this study, fluid reasoning abilities, for example, are thought to develop in part because of growth in verbal comprehension and visual spatial abilities that reciprocally influence each other. Following POT, positive interrelations mainly result from domain-general executive attentional processes that are involved in each of the domain-specific tasks.

The differences in strength of connectivity between networks can be interpreted in light of ability differentiation, where higher cognitive ability is associated with weaker correlations between cognitive tests (Spearman, 1927). This was indeed shown in our study: connectivity was stronger in VP than in FT born children, as well as in VP children with below-average IQ compared to VP children with average-high IQ. Support for ability differentiation in children in the literature is scarce and inconsistent due to varying methodological approaches. In a systematic review, Breit et al. (2021) made a distinction between grouping and model-based methods. In grouping methods, the sample is usually split into high and low ability groups to compare average intercorrelations. Such approaches have been criticised for the arbitrary division of the cognitive ability spectrum, bringing forth the concern that results may be biased by irrelevant chosen cut-off points. To overcome this, model-based methods using confirmatory factor analysis have been developed. Studies using grouping methods showed mixed findings, whereas four of five more recent model-based studies found consistent support for ability differentiation. Furthermore, Breit et al. (2021) found differentiation effects for verbal but not figural and numeric factors, suggesting that ability differentiation might be domain specific. However, these studies used factor models to model intelligence, which may limit a direct comparison with our findings obtained using psychometric network analysis and comparing VP, FT, below-average, and average-high IQ groups. One explanation for the more differentiated cognitive structure in children with higher levels of intelligence is offered by POT. According to this theory, executive processes serve as bottlenecks, constraining performance across tests and giving rise to the positive manifold. The bottleneck effect becomes stronger with decreasing levels of EF, resulting in higher correlations between tests (Kovacs & Conway, 2019). VP born children are at risk for deficits in EF and attentional control processes (Brydges et al., 2018; Twilhaar, Belopolsky, de Kieviet, van Elburg, & Oosterlaan, 2020; Twilhaar, de Kieviet, van Elburg, & Oosterlaan, 2020; Van Houdt, Oosterlaan, van Wassenaer-Leemhuis, van Kaam, & Aarnoudse-Moens, 2019). These deficits have been found to underlie lower IQ and academic performance in VP compared to FT born children (Twilhaar, Belopolsky, et al., 2020; Twilhaar, de Kieviet, et al., 2020).

Network analysis has also been used to study the brain connectome, where nodes correspond to voxels or regions of interest and edges represent structural or functional associations between pairs of nodes (Wang, Zuo, & He, 2010). Preterm birth has been found to affect the brain connectome. In EP and VP born school-age children, structural networks were more segregated and less integrated compared to full-term born peers, possibly resulting from white matter abnormalities (Fischi-Gomez et al., 2016; Thompson et al., 2016). Without directly studying this link, it remains speculative how the cognitive networks in our study relate to the alterations in brain connectivity in VP born children. Based on a behaviour-brain combined multilayer network, Simpson-Kent et al. (2021) concluded that such relations are complex and not necessarily straightforward.

Working memory had the least central role in the networks across samples, whereas verbal, processing speed, and visuospatial abilities were most central. Similar findings were shown in a cohort of 5-18-year-old children with learning difficulties (Simpson-Kent et al., 2021). This contradicts mutualism and POT, which propose (the executive component of) WM as one of the most central or domain-general processes giving rise to the positive manifold (Kovacs & Conway, 2016; van der Maas et al., 2017). However, the strength of interrelations between and importance of cognitive abilities may change throughout development. Cowan (2021) showed that the correlation between the WPPSI WM subtests and other subtests varied across ages between 2.5 and 7.6 years in a wave-like pattern. According to Demetriou et al. (2018), there are four main stages of cognitive development, in which the centrality of cognitive processes varies depending on the developmental priority of a specific stage. Attentional control, processing speed, and linguistic awareness were found to be more central and more interrelated with general ability between 5 and 8 years, whereas reasoning and WM became more important between 9 and 12 years of age (Demetriou et al., 2014; Demetriou, Mougi, Spanoudis, & Makris, 2022; Demetriou, Spanoudis, Makris, Golino, & Kazi, 2021). This might be related to the developmental trajectories of cognitive processes and their neural correlates. Whereas some processes, such as language, start to develop very early on and reach equilibrium sooner, others start to develop and reach a steady state later in life (Demetriou et al., 2022).

Indeed, research shows that WM still largely develops into adulthood, when it reaches a steady state (Funahashi, 2017; Gathercole, Pickering, Ambridge, & Wearing, 2004; Gómez et al., 2018). Brain infrastructure supporting these functions show similar trajectories. Particularly, highly centralised and strategically located regions or *hubs* are initially located in primary networks, including the sensorimotor, visual, and auditory networks, but move toward regions implicated in higher-order cognition later in life (Cao, Huang, & He, 2017; Zhao, Xu, & He, 2019). In line with aforementioned studies, we have shown that verbal and processing speed abilities are more central in early childhood, reflecting the cognitive demands at that stage as suggested by Demetriou et al. (2018), whereas WM may become more central later on, as shown in the adult network of intelligence (Schmank et al., 2019). In contrast to the present findings, WM and attentional control processes were found to play an important role in impairments in intelligence and academic performance in VP born adolescents (Twilhaar, Belopolsky, et al., 2020; Twilhaar, de Kieviet, et al., 2020). Altogether, the incompatibility of our findings to mutualism and POT demonstrates the need for further theory development, integrating findings from cognitive and biological sciences, while also taking developmental dynamics into account. The theory of evolving networks of human intelligence (Savi, Marsman, & van der Maas, 2021) presents such a multilevel and dynamical view on intelligence and should be considered in future research.

In VP born children with below-average intelligence levels, processing speed had a particularly strong connection with other abilities, which was not found in VP children with average-high intelligence levels. In light of POT, this may indicate that processing speed may function as a bottleneck in VP children with impaired intelligence by restricting performance in tests of other abilities, resulting in lower overall test performance. Rather than the level of processing speed per se, the extent to which it is linked to other cognitive abilities seems particular to this group. However, Clark et al. (2014) showed limited discrimination between processing speed and attentional control processes in pre-schoolers. Moreover, WPPSI processing speed subtests tap multiple processes, including attentional control. VP birth is associated with attentional control deficits and impaired task performance mainly when attentional control demands are high (Twilhaar, Belopolsky, et al., 2020; Twilhaar, de Kieviet, et al., 2020; Twilhaar, de Kieviet, van Elburg, & Oosterlaan, 2019). This suggests that the strong interrelatedness of processing speed with other tasks may in part be explained by the overlapping demands of these tasks on attentional control processes. Further research into these relations is needed.

The present study contributes to the literature by using a novel approach according to contemporary views on intelligence, allowing for individual differences. To our knowledge, it is the first application of psychometric network analysis to WPPSI-IV data in large population-based neurotypical (FT) and neurodiverse (VP) groups. Our study also has several limitations. Firstly, selective drop-out of children from less favourable social backgrounds and children with disabilities limits generalizability of our findings. Similarly, weighting procedures to correct for non-representativeness of the FT sample (Charles et al., 2020) were incompatible with network analyses. Unequal sample sizes limit a direct visual comparison between the networks in Figures 2 and 3. Moreover, stability decreased in networks with smaller sample sizes, resulting in larger variability in edge-weight estimation and less accurately estimated overall strength. Further studies with reasonable sample sizes are therefore warranted to replicate our findings. Although our findings can be interpreted in line with ability differentiation, our study should not be seen as a direct test of this hypothesis, because of the disadvantages associated with grouping based on IQ (Breit et al., 2021). Furthermore, the cross-sectional analyses did not take the dynamic character of intelligence, as proposed by the mutualism model, into account. Regarding centrality, we only focused on strength centrality since other centrality indices are generally unstable (Bringmann et al., 2019). This limits our comprehension of the networks' most important abilities. Lastly, connections between abilities describe partial correlations rather than causal interactions, as proposed by mutualism. Therefore, it remains to be further explored whether interventions targeting central abilities would lead to meaningful improvements in other abilities.

Despite these limitations, our findings have several important implications. Cognitive abilities are strongly interrelated in early childhood, particularly in children with difficulties. This means that VP born children with below-average intelligence levels are likely to suffer from difficulties across multiple cognitive domains. The differences in network strength between VP and FT born children do not seem to be specific to VP birth, as no differences were observed in cognitive networks of VP and FT born children that were matched on IQ. As suggested before by Tucker-Drob (2009), the more differentiated cognitive structure at higher levels of intelligence implies that composite IQ scores may not well reflect domain-specific abilities. This is particularly relevant for VP born children. Our matched subsample still showed lower levels of processing speed and visuospatial abilities in VP compared to FT born children, despite similar FSIQ scores. Such specific difficulties may be masked when focusing on general ability (i.e., FSIQ). This emphasises the importance of assessing specific abilities in addition to general cognitive ability in VP born children, both in clinical and research settings. At 5.5 years of age, verbal and processing speed abilities and not WM were the most central abilities. This suggests that efforts to promote the development of these abilities may benefit the development of other cognitive abilities. This requires longitudinal research to study the dynamics of the relations shown in the present cross-sectional networks and whether improvement of certain abilities actually leads to improvement of other abilities. Kievit et al. (2017) and Kievit, Hofman, and Nation (2019) showed that children (6–8 years) and adolescents (14–25 years) with better vocabulary subsequently showed larger gains in reasoning ability. This mutualistic coupling was strongest in young children (Kievit et al., 2019) and emphasises the importance of verbal abilities as a building block for the development of other cognitive abilities in early childhood, as also suggested by our findings and Demetriou et al. (2021, 2022). Although further research is required, verbal abilities seem an important target for early interventions to improve cognitive outcomes after VP birth.

Conclusions

At 5.5 years of age, cognitive abilities are densely positively interrelated in both VP and FT born children. This was particularly true for children with lower levels of intelligence. Our study confirmed the value of psychometric network analysis for studying cognition in neurotypical and neurodiverse groups of children and highlights the importance of considering the interrelatedness of cognitive abilities in future studies. The present analyses should be extended by longitudinal network analyses to consider the dynamics of cognitive development and to provide further crucial knowledge for the development of interventions.

Supporting information

Additional supporting information may be found online in the Supporting Information section at the end of the article:

Table S1. Correlation Matrix.
Table S2. Fit statistics for estimated network models.
Table S3. Node-predictability indicated by the explained variance (R^2) across networks.

Table S4. Comparison of WPPSI-IV scores between very preterm (VP) and full-term (FT) born children who were matched on full-scale IQ.
Figure S1. 95% bootstrapped confidence intervals of estimated edge-weights for the estimated networks of cognitive abilities for the very preterm sample (A), full-term sample (B), very preterm sample with below-average IQ (C), and very preterm sample with average-high IQ (D).
Figure S2. Bootstrapped difference tests ($\alpha < .005$) for node strength of the ten cognitive abilities for the very preterm sample (A), full-term sample (B), very preterm sample with below-average IQ (C), and very preterm sample with average-high IQ (D).
Figure S3. Stability of strength centrality for the very preterm sample (A), full-term sample (B), very preterm sample with below-average IQ (C), and very preterm sample with average-high IQ (D).
Figure S4. Network models of cognitive abilities for very preterm and full-term born children who were matched on IQ.

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Key points

- Very preterm birth is associated with a high risk for cognitive impairments, but there are large interindividual differences. Underlying mechanisms of these differences remain to be elucidated.
- Cognitive abilities are positively correlated with each other, but the strength of interrelations varies between individuals. According to the ability differentiation hypothesis, interrelations are weaker at higher levels of ability.
- At 5.5 years of age, cognitive abilities form a network of strongly interrelated abilities in both very preterm and full-term born children.
- Cognitive abilities were more strongly interconnected in children with lower intelligence levels.
- Composite intelligence scores may mask deficits in domain-specific abilities, particularly in children at risk for cognitive impairments, e.g., those born very preterm, even when general intelligence levels are unimpaired.

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