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Abstract

Children and adolescents with neurodevelopmental disorders (NDDs) demonstrate extensive cognitive heterogeneity that is not adequately captured by traditional diagnostic systems. Using a transdiagnostic approach, a retrospective cohort study of cognitive functioning was conducted with a large heterogenous sample (*n* = 1529) of children and adolescents 7 to 18 years of age with NDDs. Measures of short-term memory, verbal ability, and reasoning were administered to participants with attention-deficit/hyperactivity disorder (ADHD), autism spectrum disorder (ASD), comorbid ADHD/ASD, and typically developing (TD) participants using a 12-item web-based neurocognitive testing battery. Unsupervised machine learning techniques were implemented to create a self-organizing map (SOM), an artificial neural network, in conjunction with k-means clustering algorithms to identify data-driven subgroups. Six clusters representing different cognitive profiles were identified, including participants with varying degrees of cognitive impairment. Diagnostic status did not correspond with cluster-membership, providing evidence for the application of transdiagnostic approaches to understanding cognitive heterogeneity in children and adolescents with NDDs. Additionally, the findings suggest that many TD participants may have undiagnosed learning difficulties, emphasizing the need for accessible cognitive assessment tools in school-based settings.

Keywords: transdiagnostic, machine learning, cognition, neurodevelopmental disorders, autism spectrum disorder, attention-deficit/hyperactivity disorder, learning difficulties

A Transdiagnostic Examination of Cognitive Heterogeneity in Children and Adolescents with Neurodevelopmental Disorders

The acquisition and refinement of advanced cognitive processes throughout childhood and adolescence represents a critical aspect of development, ultimately shaping how individuals understand and interact with the environment around them. Broadly defined as the ability to perform higher-level mental processes associated with learning, memory, attention, and reasoning, cognitive functioning demonstrates considerable heterogeneity amongst those with neurodevelopmental disorders (NDDs), thus confounding research and clinical practice (Larsen & Luna, 2018; Márquez-Caraveo et al., 2021).

Characterized by an onset in the developmental period, NDDs comprise a diverse group of psychological conditions associated with developmental deficits that produce impairments of personal, social, academic, or occupational functioning (American Psychiatric Association, 2013). Among the most frequently diagnosed NDDs are attention-deficit/hyperactivity disorder (ADHD), and autism spectrum disorder (ASD), impacting approximately 5–11% and 1–3% of the global population under 18 years old, respectively (Francés et al., 2022). Both ADHD and ASD are highly heritable and frequently co-occurring NDDs (Ames & White, 2011; Coghill & Sonuga-Barke, 2012; Willcutt & Pennington, 2002) with estimated comorbidity rates of 30–70% (Brookman-Frazee et al., 2018; Joshi et al., 2017; Lyall et al., 2017).

The distinguishing features of ADHD, including inattention and hyperactivity are commonly observed in children with ASD (Arnett et al., 2018; Sokolova et al., 2017; van Steijn et al., 2012), and interestingly, many individuals with these conditions demonstrate similar impairments in executive functioning (Barkley, 1997; Bloemen et al., 2018; Castellanos-Ryan et al., 2016; Pennington & Ozonoff, 1996). In this population, learning difficulties are highly prevalent and often attributed to deficits in executive functioning, with approximately 44% of children with ADHD and 65–85% of children with ASD exhibiting concurrent learning difficulties (Gillberg & Coleman, 2000; Pastor & Reuben, 2008). Current research indicates that both independent and co-occurring diagnoses of ADHD and ASD are linked to impairments in several domains of cognitive functioning, such as working memory and attention (Follmer, 2018; Holmes et al., 2021a; Landerl & Kölle, 2009; Peng & Fuchs, 2016; Peng et al., 2018; Yeniad et al., 2013), leading many children to experience significant challenges at school (Booth & Happé, 2010; Corbett et al., 2009; Karalunas et al., 2018; Rosello et al., 2022).

Considering the well-documented relationship between cognitive development and future academic performance (Peng & Kievit, 2020; Nesayan et al., 2019), the early identification and treatment of cognitive deficits in this population remains a fundamental concern to researchers and clinicians alike (e.g., Craig et al., 2016; Young et al., 2020; Zhang et al., 2020). Although best addressed through high-quality education, cognitive therapies, and nutrition during the formative years of development (Burger, 2010; Jirout et al., 2019), there are numerous obstacles impeding proactive approaches. Namely, the extent to which traditional diagnostic systems are not conducive to variations in symptomology within diagnostic groups, and the inaccessibility of cognitive assessments (Finlay-Jones et al., 2019; MacDonald & Deacon, 2019; Mandell et al., 2009). The present study seeks to overcome these limitations by utilizing *Creyos*, an accessible web-based neurocognitive testing battery to identify the cognitive profiles of children and adolescents with NDDs, including those with ADHD, ASD, and comorbid ADHD/ASD on assessments of short-term memory, verbal ability, and reasoning. Transdiagnostic approaches will be implemented to examine the extensive cognitive heterogeneity that exists within this population, with emphasis on informing the provision of appropriate school-based interventions.

Limitations of Traditional Diagnostic Nosologies:

The dominant categorical approach to classification in the *DSM-5* and the *ICD-11* has widely-recognized limitations in neurodevelopmental research, particularly as it pertains to investigations into abnormal cognitive processing (American Psychiatric Association, 2013; Aoki et al., 2017; Baribeau et al., 2019; Krakowski et al., 2020; Kushki et al., 2019; World Health Organization, 2019). These challenges arise because traditional diagnostic systems tend to endorse a core-deficit model of psychopathology, thus warranting the categorization of psychological disorders according to a single neurocognitive deficit (Astle & Fletcher-Watson, 2020). This model posits that core deficits (i.e., impairments derived from a common etiological origin) give rise to specific clusters of cognitive, behavioural, and neurobiological attributes (Astle & Fletcher-Watson, 2020), however, growing evidence would suggest otherwise.

Research conducted on the diverse symptom presentation of NDDs within and across diagnostic categories has consistently provided support for the phenomenon of equifinality (Bishop, 1997), arguing that similar developmental profiles may emerge from the complex interaction of different causal factors, rather than a single core deficit (de la Torre-Ubieta et al., 2016; Gizer et al., 2009; Happé et al., 2006; Hawi et al., 2015; Li et al., 2014; Neale et al., 2010; Pennington, 2006; Vorstman et al., 2017). For example, the theory-of-mind hypothesis of ASD, which refers to the impaired capacity of individuals with ASD to understand the mental states of others, has been contradicted by findings that suggest these impairments may be limited to interactions with non-autistic people rather than similar others, thus representing a source of miscommunication across sociocultural groups instead of a core deficit (Crompton et al., 2020; Edey et al., 2016). Correspondingly, evidence for multifinality (Cicchetti & Rogosch, 1996), which proposes that specific neurobiological abnormalities may give rise to different patterns of impairment rather than highly selective deficits (Ameis et al., 2016; Anagnostou & Taylor, 2011; Lenet, 2017; Lichtenstein et al., 2010; Lionel et al., 2014; Ronald et al., 2008; Rommelse et al., 2010; Wang et al., 2017) has been supported by research linking heterogenous cognitive profiles to particular neural substrates (Siugzdaite et al., 2020). Therefore, even voxel-wise neuroimaging techniques may not be appropriate for examining cognitive deficits associated with conventional NDD diagnoses, because these approaches do not capture the dynamic interaction that occurs between brain regions throughout development (Johnson, 2011; Karmiloff-Smith, 2009).

Additionally, strict adherence to traditional diagnostic nosologies has particularly harmful consequences for children and adolescents with co-occurring NDDs, heterogenous cognitive profiles, and symptomology that fails to reach prescribed diagnostic thresholds (Coghill & Sonuga-Barke, 2012). Considering the high rates of comorbidity (Faraone et al., 1998; Willcutt & Pennington, 2000; Coghill & Sonuga-Barke, 2012) and heterogeneity that exist within and across NDD diagnoses (Ameis et al., 2017; Willcutt & Pennington, 2000; Rommelse et al., 2010; van der Meer et al., 2017), categorical classification systems may not adequately capture the full population of children that require supports at school, and may not effectively inform the provision of school-based interventions according to students' specific learning challenges.

Under the categorical one-size-fits-all approach to classification, individuals with symptoms that deviate from strict diagnostic criteria run the risk of remaining undiagnosed and underserved, regardless of how debilitating their NDD-related learning or cognitive disabilities may be (Bathelt et al., 2018; Holmes et al., 2019; Siugzdaite et al., 2020). Among the smaller portion of children with learning difficulties who meet the criteria for a clinically-recognized NDD, barriers to accessing appropriate interventions are also pervasive (Ono et al., 2019). As there is rarely consideration for variability in cognitive performance within diagnostic groups in experimental research, subsequent treatment recommendations are unlikely to address the needs of all individuals within a single diagnostic category (Antshel & Russo, 2019; Karalunas et al., 2018). Furthermore, the generalizability of categorical-based research is further called into question when considering that individuals with co-occurring diagnoses are often excluded from participant samples, thus alienating a significant portion of the population, and causing the literature to overstate the purity of NDDs (Arnett et al., 2018; Sokolova et al., 2017; van Steijn et al., 2012). The tendency to use stringent exclusionary criteria also overemphasizes within-group homogeneity and individual differences in the sample, which may constitute a barrier to understanding neurodiversity in children with cognitive impairments (Fletcher-Watson, 2022).

The Inaccessibility of Cognitive Assessments:

Concerns regarding the accessibility of diagnostic instruments, specialized personnel, and appropriate interventions represent an additional limitation of current diagnostic techniques. Many studies suggest that the inaccessibility of cognitive assessments is amplified by systematic barriers related to racial, ethnic, gender, and socioeconomic factors (Constantino et al., 2020; Tek & Landa, 2012; Williams et al., 2022; Zuckerman et al., 2017). This is evidenced by the finding that non-white children from low-income households are less likely to be identified and to receive a timely diagnosis of ASD compared to their historically-advantaged counterparts (i.e., white children from high-income households), despite the prevalence of ASD remaining relatively consistent across demographic groups. (Aylward et al., 2021; Mandell et al., 2007; Wiggins et al., 2020). Furthermore, a comprehensive meta-analysis examining prospective and longitudinal research on the disparities in accessing ADHD diagnoses found that girls were less likely receive an ADHD diagnosis in childhood compared to boys (Hinshaw et al., 2022). It is postulated that because girls with ADHD tend to demonstrate more inattentive than hyperactive symptoms, the disorder goes undetected for longer, as clinicians may be more accustomed to the classic symptom presentation in boys (Hinshaw et al., 2022; Mowlem et al., 2019; Quinn & Madhoo, 2014; Young et al., 2020). Consequently, young girls may experience more challenges at school because the delayed diagnosis and treatment of ADHD has been found to predict low educational attainment, especially for those with predominantly inattentive symptoms (Polderman et al., 2010; deZeeuw et al., 2017). Similar insights were obtained from research examining minority-status groups, finding that delays in accessing appropriate interventions predicted greater learning difficulties (Marlow et al., 2019), thus emphasizing the need for better approaches to the identification and treatment of cognitive impairments that characterize NDDs.

A Promising Alternative – Transdiagnostic Approaches:

To address the limitations of traditional diagnostic systems, there has been growing interest in using transdiagnostic approaches to capture the large heterogenous population of children and adolescents with NDDs (Cuthbert & Insel, 2013; Owen, 2014). Transdiagnostic approaches use multivariate data reduction techniques to generate simple mixed-sample models of multidimensional data, which contrasts with the univariate approaches often used to analyze categorical frameworks with singular discrete constructs (Astle et al., 2022; Bathelt et al., 2018). This theoretical model capitalizes on multiple overlapping dimensions that correspond with broad latent constructs, along which individuals can be located (Astle et al., 2022; Bathelt et al., 2018). In using a quantitative classification system, the relationship observed between dimensions may be used to determine the mechanisms responsible for shared or unique variance, and how extensive variability translates into observable behaviour (Holmes et al., 2021a; Parkes et al., 2020). Complementary clustering techniques may also be implemented to identify discrete subpopulations of individuals within broad multidimensional space, which may provide insight into the underlying organizational properties of the data, thereby eliminating the need for traditional diagnostic boundaries (Astle et al., 2022; Siugzdaite et al., 2020).

According to this model, NDDs may be best conceptualized in terms of multiple continuous dimensions related to cognition, with levels ranging from typical to atypical functioning, allowing for a continuity of clinical features rather than strict binarization (Bathelt et al., 2018; Holmes et al., 2019). Therefore, individuals may demonstrate atypical functioning across multiple cognitive dimensions, such that their concurrent combination indicates the presence of more severe learning difficulties (Astle et al., 2022). In this context, the focus is directed towards identifying underlying cognitive symptoms that are responsible for the emergence of learning difficulties, under the notion that endophenotype (i.e., quantifiable measures on a continuous scale, not directly accessible to observation without standardized testing) influences phenotype (i.e., observable features of the disorder) such as academic achievement (Casey et al., 2014; Zhao & Castellanos, 2016; Peng & Fuchs, 2016).

The Transdiagnostic Revolution:

Aptly denoted the “Transdiagnostic Revolution” by Astle and colleagues (2022), dimensional approaches are increasingly being used to promote applications of the neurodiversity paradigm in the developmental sciences (Fletcher-Watson, 2022; Sonuga-Barke et al., 2016). As strong advocates at the forefront of this movement, the Centre for Attention, Learning and Memory (CALM) team at the University of Cambridge has made impressive strides towards elucidating the dynamic nature of neurodevelopmental disorders across neural (Akarca et al., 2021; Astle et al., 2019; Bathelt et al., 2019; Jones et al., 2022), intellectual (Simpson-Kent et al., 2021), behavioural (Bathelt et al., 2018; Bathelt et al., 2021; Jones et al., 2021), communicational (Mareva et al., 2019), socioemotional (Mareva et al., 2023), psychopathological (Bryant et al., 2020; Guy et al., 2022; Holmes et al., 2021b) and cognitive domains of functioning (Holmes et al., 2019; Holmes et al., 2021a; Mareva et al., 2022; Suigzdaite et al., 2020; Williams et al., 2022). Furthermore, many non-affiliated researchers have made significant contributions, implementing transdiagnostic approaches towards understanding the heterogeneity of learning difficulties among children and adolescents (e.g., Archibald et al., 2013; Child et al., 2019; Doi et al., 2022; Grzadzinski et al., 2013; Martel et al., 2010; Leung & Chan, 2016; Poletti et al., 2018; Ramus et al., 2013; Roberts et al., 2017).

The strengths associated with implementing a transdiagnostic approach in investigating neurodevelopmental disorders has been emphasized by many researchers (e.g., Alexander et al., 2017; Astle et al., 2022; Casey et al., 2014; Coghill & Sonuga-Barke, 2012; Fletcher-Watson, 2022; Zheo & Castellanos, 2016) and most prominently, by the National Institute for Mental Health (NIMH) via the Research Domain Criteria (RDoC) framework for investigating mental disorders (Cuthbert & Insel, 2013), and the Hierarchical Taxonomy of Psychopathology (HiTOP) model, which serves as a dimensional alternative to traditional diagnostic nosologies (Kotov et al., 2017). A notable advantage associated with dimensional constructs is the ability to challenge conventional boundaries between diagnostic categories. For instance, many researchers theorize that ADHD and ASD are unique manifestations of one NDD along a single continuum, given that they share many pathophysiological similarities (Rommelse et al., 2011; van der Meer et al., 2012), therefore, a transdiagnostic framework allows for parsing between these conventional boundaries. Furthermore, embracing dimensionality provides an opportunity to tease apart different cognitive subtypes that may be embedded within clinically-recognized NDDs, as evidenced by researchers who have used clustering algorithms to identify distinct learning (Archibald et al., 2013) and behavioral profiles (Bathelt et al., 2018) that cut across diagnostic boundaries. These findings have practical applications as well, such that it may facilitate the stratification of individuals to appropriate intervention services that address the specific cognitive impairments that are contributing to one's learning difficulties.

These approaches are beginning to be implemented with cognitive data, but remain in their relative infancy (Boulton et al., 2021). Astle and colleagues (2019), for example, were the first researchers to apply machine learning to investigate heterogeneity in a large sample of struggling learners using cognitive, behavioural, and neuroimaging data. From their analysis using a self-organizing map with data from over 500 participants, they identified four distinct cognitive profiles that were not significantly predicted by diagnostic status or referral reason (Astle et al., 2019). A self-organizing map is a type of artificial neural network whose algorithm attempts to learn about the underlying structure of data itself, rather than which data corresponds to predefined groups, therefore, these findings suggest there is extensive heterogeneity across the cognitive profiles of children and adolescents with learning difficulties (Astle et al., 2019).

Similar findings were also obtained by Suigzdaite and colleagues (2020), who took a dimensional approach to establishing how brain structure relates to cognitive challenges in childhood. The researchers submitted cortical morphology, learning, and cognitive data from approximately 500 participants to a self-organizing map, and similarly identified four profiles that did not correspond with the formal diagnostic status of participants (Suigzdaite et al., 2020). These studies, however, are not without limitations. Firstly, because the continuous mapping process is not confined by clear boundaries, developing a strong rationale regarding the formation of transdiagnostic groups becomes quite difficult. Additionally, both aforementioned studies used relatively low sample sizes, meaning their analyses may have lacked sufficient power to detect more nuanced group differences, with only the largest and most consistent differences between groups being identified. They also exclusively relied on data obtained from formal psychoeducational testing, thus presenting concerns regarding the generalizability of these findings, considering that in-person cognitive assessments are largely inaccessible and thus excludes a significant proportion of the target population.

The Present Study:

A retrospective cohort study of cognitive functioning was conducted using a large heterogenous sample (*n* = 1529) of children and adolescents 7 to 18 years of age. Measures of short-term memory, verbal ability, and reasoning were administered to participants with ADHD, ASD, comorbid ADHD/ASD, as well as TD participants using a 12-item neurocognitive testing battery. The objectives of the present study were to identify cognitive profiles in the sample and to determine their correspondence with traditional diagnostic status.

Given that there is rich neurodiversity among children and adolescents with learning difficulties, it was hypothesized that an unspecified number of cognitive profiles would emerge from the dataset that cut across diagnostic boundaries, based on participants' relative strengths and weaknesses in different domains of cognitive functioning. It was also hypothesized that the cognitive profiles identified would not correspond with participants' formal diagnostic status because the transdiagnostic approach will capture the extensive variability in symptomology that exists within and across conventional NDD diagnoses. Unlike previous research, the present study examined a substantially larger heterogenous sample, and analyzed cognitive assessments administered on *Creyos*, a web-based neurocognitive battery, rather than relying on in-person cognitive assessments which are largely inaccessible. The cognitive profiles that emerged from the sample may be used to inform the provision of school-based interventions by accounting for children's strengths and weakness across different domains of cognitive functioning.

Method

Participants

No recruitment or compensation procedures were implemented in the present study. The dataset consisting of both cognitive and demographic information was previously collected by researchers at Brain Balance Achievement Centers between March 2019 and October 2020 from various sites across North America. Data was initially collected to assess the efficacy of the Brain Balance Program, an integrative and multimodal training initiative that aims to improve cognitive performance among children and adolescents with learning difficulties.

A sample of 1529 participants (1024 boys and 505 girls) between the ages of 7 and 18 years old (*M* = 10.60 years, *SD* = 2.69 years) was obtained from a larger dataset of over 10000 participants, with inclusion criteria that extended to capture residents of North America and fluent English speakers. Additionally, it was determined that participants in the typically developing group had not been diagnosed with any psychological disorder(s) or motor difficulties (i.e., significant gross motor difficulties and/or motor skill disorders, as diagnosed by a physician). Participants in the experimental group were required to have a diagnosed neurodevelopmental disorder (i.e., Attention-Deficit/Hyperactivity Disorder, Autism Spectrum Disorder) and no comorbid condition(s) that would impact cognitive functioning (e.g., Intellectual Disability, Global Developmental Delay).

Subsequently, four groups were identified, including 510 participants with ADHD (360 boys and 150 girls, M_{age} = 11.39 years) 42 participants with ASD (36 boys and 6 girls, M_{age} = 12.40 years), 42 participants with comorbid ADHD/ASD (35 boys and 7 girls, M_{age} = 13.03 years), and 935 Typically Developing (TD) participants (593 boys and 342 girls, M_{age} = 10.50 years). A consort diagram can be found in Appendix A.

Materials

Online Cognitive Tests

The online cognitive tests administered through the research platform *Creyos* (see Appendix B) consist of an extensively-validated 12-item battery that measures short-term memory, reasoning, and verbal ability (Hampshire et al. 2012; Owen et al., 2010). The assessment takes approximately 40 minutes to complete, and each task has been "gamified" to maintain participant interest. Before each task, written instructions are displayed to participants in paragraph form. No other instructional material is provided, and the tasks are designed to be self-administered. Cognitive performance is reflected in participants' scores across 66 relevant performance measures, including final score, maximum score, average score, number of attempts, number of correct responses, number of errors, and reaction time for each task.

The *Creyos* platform is routinely used to administer online cognitive tests to children, adolescents, and adults – including children as young as 4 years old and children with neurodevelopmental disorders. Since its inception, *Creyos* has accumulated a database of roughly 4.5 million scores from over 400,000 users, with 75,000 of these scores being used to establish associations between task performance and IQ (Hampshire et al., 2012). The cognitive tasks have been validated in several large-scale studies examining healthy controls and patient populations. For example, researchers have observed that results from the *Creyos* battery were comparable that of the Wechsler Adult Intelligence Scale Revised (WAIS-R), a standard 2–3-hour neuropsychological battery (Levine et al., 2013), and that the Creyos battery outperformed the Montreal Cognitive Assessment (MoCA), a standard task of cognitive abilities in assessing capacity in the elderly (Brenkel et al., 2017). Test-retest reliability calculated from a population sample (N = 12,463) collected on the *Creyos* website revealed an average Pearson's correlation of $r = 0.69$ across the 12 cognitive tasks and learning effects of 3.16 (% improvement) between session one and session two, indicating high levels of reliability (Creyos, n.d.). Descriptions of each cognitive task used in the assessment can be found below (Wild et al., 2018):

Paired Associates (PA). A puzzle-based assessment routinely used to detect impairments of memory in aging clinical populations (Gould et al., 2005). At the beginning of the task, several boxes appear on the screen in a randomly distributed manner, and one-by-one, each box opens to reveal a different icon (e.g., cube, windmill, envelope, etc.). Users are instructed to remember which icons correspond with each box, and upon being presented with each icon sequentially, they must indicate which box the icon initially appeared in. If participants correctly identify all the icon-location pairs, the difficulty level of the task increases, such that one additional box appears in the next trial. However, if an identification error is made, subsequent trials will contain one less box. The task continues until three errors are made, and the user's final score is calculated based on the number of paired associates successfully remembered. A population sample ($N = 1131$) collected from the *Creyos* website provides evidence for high test-retest reliability, revealing a Pearson's correlation of $r = 0.45$ and learning effects of -0.38 (% improvement) between session one and session two (Creyos, n.d.).

Digit Span (DS). An adaptation of the verbal working memory component of the Weschler Adult Intelligence Scale Revised (WAIS-R; Weschler, 1981). After observing a sequence of digits that appear on the screen in green-coloured ink, users are instructed to reproduce the sequence in the correct order using an on-screen keyboard. The difficulty level of the task progressively increases with each successful trial, such that the digit sequence increases in length. Otherwise, unsuccessful attempts cause the sequence to decrease in length. The task continues until three mistakes are made (i.e., the digit sequence is recalled incorrectly on three separate occasions), and the longest digit sequence successfully reproduced reflects final scores. Evidence for high test-retest reliability was obtained from a population sample (*N* = 1022) collected on the *Creyos* website, which revealed a Pearson's correlation of *r* = 0.64 and learning effects of 1.33 (% improvement) between session one and session two (Creyos, n.d.).

Feature Match (FM). An assessment used to measure attentional processing, based on classical feature search tasks (Treisman & Gelade, 1980). In this task, two boxes are displayed side-by-side on the screen, with each containing an assortment of shapes. Users are instructed to determine whether the contents of the two boxes are identical or different (i.e., whether each shape and their relative positions match, or differ by just one item) by selecting the 'match' or 'mismatch' options. Over the course of 90 seconds, participants must complete as many trials as possible. Following each correct response, an additional shape is added to the next trial, whereas incorrect responses result in the removal of one shape from subsequent trials. Final scores are calculated based on how many correct responses are provided, minus the incorrect responses. Test-retest reliability calculated from a population sample (*N* = 1132) collected on the *Creyos* website revealed a Pearson's correlation of *r* = 0.57 and learning effects of 4.09 (% improvement) between session one and session two, indicating high reliability (Creyos, n.d.).

Spatial Planning (SP). A measure of executive functioning based on the Tower of London Task (Shallice, 1982). Participants are presented with a tree-shaped diagram that is lined with circles numbered one through nine and must rearrange the diagram so that the circles are placed in ascending numerical order. The green-coloured circles are used to identify numbers placed in the correct location, whereas the red-coloured circles represent numbers that are placed in the incorrect location. To reorganize their positions, users must select a circle to take it off the end of a branch, and then select the spot where they would like it placed. The trials progressively increase in difficulty, and a successfully completed puzzle boosts their final score by the following metric: ((2 x minimum number of moves required to solve the puzzle) – the number of moves made). Participants are allocated three minutes to solve as many puzzles as possible. A Pearson's correlation of $r = 0.87$ and learning effects of 3.75 (% improvement) between session one session two indicates high test-retest reliability, as evidenced from a population sample ($N = 1150$) collected on the *Creyos* website (Creyos, n.d.).

Polygons (PO). A variation of the Interlocking Pentagons Task, which is commonly used to assess visuospatial processing and detect age-related disorders (Folstein et al., 1975). Users are presented with two overlapping polygons on the left side of the screen, and a single polygon positioned on the right. They must indicate whether the single polygon is identical to either of the two overlapping polygons by selecting 'match' or 'mismatch.' Each correct response increases their score by an amount equal to the difficulty level of the trial, and vice versa occurs with each incorrect response. Throughout the task, the trials progressively increase in difficulty, such that the differences between polygons become more subtle, thus making them more difficult to distinguish. Final scores reflect the number of correct identifications made in 90 seconds. A population sample ($N = 905$) collected from the *Creyos* website provides evidence for high test-retest reliability, revealing a Pearson's correlation of $r = 0.60$ and learning effects of 7.91 (% improvement) between session one and session two (Creyos, n.d.).

Monkey Ladder (ML). A visuospatial working memory task derived from non-human primate literature (Inoue & Matsuzawa. 2007). In this task, numbered boxes are simultaneously displayed across random locations on the screen for a limited amount of time (i.e., number of boxes x 90 milliseconds), after which the numbers disappear and only the boxes remain. Users are instructed to select the boxes in ascending numerical order and obtain a final score based on the length of the longest sequence remembered. The difficulty of each trial varies dynamically, such that correct responses are followed by trials with an additional digit, and incorrect responses are followed by trials that have one less digit. There is no time limit for answering, however, the assessment ends after three mistakes are made. Evidence for high test-retest reliability was obtained from a population sample (N = 804) collected on the *Creyos* website, which revealed a Pearson's correlation of r = 0.57 and learning effects of 1.62 (% improvement) between session one and session two (Creyos, n.d.).

Rotations (RT). A measure of spatial manipulation ability adapted from the Spatial Rotation Task (Silverman et al., 2000). Two grids appear on the screen during the task, and each of which contains a varying number of coloured squares. One of the grids may be rotated by a multiple of 90 degrees, and participants must determine whether the grids are identical when unrotated or if they differ based on the positioning of one item. They are given 90 seconds to successfully complete as many trials as possible. Correct identifications boost the user's score by the number of squares present and adds an additional square to subsequent trials. Incorrect identifications cause the user's score to decrease by the number of squares present during that trial and removes a square from the next trial, thus making it easier to solve. Test-retest reliability calculated from a population sample (N = 1122) collected on the *Creyos* website revealed a Pearson's correlation of r = 0.70 and learning effects of 5.43 (% improvement) between session one and session two, indicating high reliability (Creyos, n.d.).

Odd One Out (OOO). A deductive reasoning task based on a subset of problems from the Cattell Culture Fair Intelligence Test (Cattell, 1949). Nine patterns appear on the screen, and users are instructed to identify which patterns differ from the rest. In each trial, the patterns are related to each other according to their common features, including colour, shape, and number of items, however, there is always one group that does not conform to these rules. Rather, participants must deduce what set of rules unify the group and select the pattern that does not match. The objective of this task is to solve as many puzzles as possible within three minutes, all while they progressively become more complex. With each correct response, the user's score increases by one, and each incorrect response causes their score to decrease by one. A Pearson's correlation of $r = 0.73$ and learning effects of 1.55 (% improvement) between session one session two indicates high test-retest reliability, as evidenced from a population sample ($N = 1138$) collected on the *Creyos* website (Creyos, n.d.).

Grammatical Reasoning (GR). An adaptation of Alan Baddeley's Three-Minute Grammatical Reasoning Task (Baddeley, 1967). This assessment of verbal memory ability features a brief written statement alongside two different shapes on the screen. For each trial, the user must indicate whether the statement reflects the characteristics of the shapes pictured below (e.g., circle is not bigger than square, square does not contain circle, etc.) by selecting either 'true' or 'false.' Each correct response increases the participant's score by one, and each incorrect response decreases their score by one. Participants are given 90 seconds to complete as many trials as possible to maximize their score. A population sample ($N = 1148$) collected from the *Creyos* website provides evidence for high test-retest reliability, revealing a Pearson's correlation of $r = 0.89$ and learning effects of 2.24 (% improvement) between session one and session two (Creyos, n.d.).

Double Trouble (DT). A modified version of the Stroop Task (Stroop, 1935) that measures cognitive inhibition. In this adaptation, a target word (either 'RED' or 'BLUE') appears at the top of the screen in red-coloured or blue-coloured ink, and the participant must select one of two probe words from the bottom of the screen that accurately describes the ink colour of the target word. The task cycles through many word-colour combinations, such that the mappings can be congruent (i.e., the description and ink colour match for all words), incongruent (i.e., either the target word or the probe words are written in the opposite colour of what they describe), or doubly incongruent (i.e., both the target word and the probe words are written in the opposite colour of what they describe). Scores are calculated based on the number of correct responses produced in 90 seconds, and incorrect answers deduct one point. Test-retest reliability calculated from a population sample (N = 1151) collected on the *Creyos* website revealed a Pearson's correlation of r = 0.92 and learning effects of 4.90 (% improvement) between session one and session two, indicating high reliability (Creyos, n.d.).

Spatial Span (SS). A spatial short-term memory tool derived from the Corsi Block Tapping Task (Corsi, 1972). This task begins with 16 purple blocks on the screen, and one-by-one, a randomly selected sequence of the blocks become green. After observing this sequence, participants are instructed to select the boxes that previously turned green in the correct order. The difficulty of the task varies dynamically, such that correct responses increase the length of the subsequent trials by one box, and incorrect responses decrease the length of the following sequence by one box. The length of the longest sequence successfully remembered during the three-minute task reflects the user's final score. Evidence for high test-retest reliability was obtained from a population sample (N = 647) collected on the *Creyos* website, which revealed a Pearson's correlation of r = 0.62 and learning effects of 0.46 (% improvement) between session one and session two (Creyos, n.d.).

Token Search (TS). Based on an assessment commonly used to measure working memory and strategy during search behaviour (Collins et al., 1998). In this task, boxes are randomly distributed around the screen, and users must click on them one-by-one to find a hidden green token. If the token is successfully located, another trial begins with an additional box on the grid, and a new token is hidden within one of the boxes. Participants are instructed to remember where previous tokens were discovered, because the new tokens are never hidden in the same location twice. If they select a box that has already been clicked or a box that previously contained the token, an error has been made and a new trial begins with one less box. This task continues until three errors are made, and the maximum level completed reflects the user's final score. A Pearson's correlation of r = 0.66 and learning effects of 4.99 (% improvement) between session one session two indicates high test-retest reliability, as evidenced from a population sample (N = 1113) collected on the *Creyos* website (Creyos, n.d.).

Demographic Questionnaire

A 29-item demographic questionnaire was completed by the child's parent(s) on Qualtrics survey software, which included questions about participants' biological sex, age, birthdate, ethnicity, medical diagnoses, or medications, social, sleep, and physical activity patterns, concentration and motivation tendencies, family income, languages spoken at home, and parents' level of education (Appendix C).

Procedure

Upon enrollment in the Brain Balance program, participants were provided with *Creyos*' Terms of Use and Privacy Policy, located on the *Creyo*s website (https://creyos.com) and the Brain Balance Privacy Policy, which can be found on the Brain Balance Achievement Centre website (https://www.brainbalancecenters.com). Consent from parents and verbal assent from youths were obtained. Participants were instructed to complete a randomized 12-item web-based cognitive assessment on Creyos, and the child's parent/guardian(s) were asked to complete a brief demographic questionnaire on Qualtrics.

Analysis

Participant responses from the cognitive assessment and demographic questionnaire were merged into a single dataset using R (Version 4.2.0) to allow for data cleaning. Incomplete responses as well as responses from participants that did not meet the prescribed inclusionary criteria were removed from the dataset. Several variables including participant age, sex, and socioeconomic status were statistically controlled for by including them as covariates in a linear regression model and extracting the residuals associated with each variable. Data visualization was performed using box plots, and rows containing outliers were removed from the dataset.

Unsupervised machine learning techniques were used to create a self-organizing map (SOM; Kohonen, 1989), an artificial neural network that yields data-driven subgroups independent of formal diagnostic status. Within the model, each node (or neuron) represents a unique cognitive profile, and spatially nearby nodes represent similar cognitive profiles. Therefore, the nodes should group together categorically if diagnoses are predictive of cognitive profiles learned by the network, while also demonstrating heterogeneity within groups.

The SOM of size 10x10 with a hexagonal topology and bubble neighbourhood function was trained using 1529 observations, such that each node was randomly assigned a weight vector with the same dimensionality as the input data. A 10x10 grid of nodes was used to replicate the statistical parameters outlined by Astle and colleagues (2020) in previous research, which follows the guideline of having the number of nodes equal to approximately five times the square root of the number of observations (Tian et al., 2014). A hexagonal topology was used to preserve topographical distances between the nodes and to reduce distortion from mapping, thus allowing for accurate interpretations of the relationships between the input data and the nodes.

The input data was submitted to the SOM to allow for similarity calculations between the input data and each node using sum of squares. Then, the node with the closest weight vector to the input data was selected by the SOM as the best-matching unit (BMU), while the weights associated with the neighbourhood of nodes were adjusted to be closer to the value of the input data. This step was accomplished using a learning rate of $\alpha = 0.05$, a standard SOM parameter, that progressively decreases over time, which allows the weights to gradually converge toward the input data. The bubble neighbourhood function ensures that nodes closer to the BMU are given higher weights, whereas nodes further away are assigned lesser weights.

To identify data-driven clusters, node weight values from the SOM were submitted to the k-means clustering algorithm, such that each node had 66 weights associated with it, corresponding to relevant performance measures from the 12 cognitive tasks. The number of clusters identified was informed by visual examinations of the data with scree plots (i.e., eigenvalues plotted as a function of the number of clusters) and the elbow method (i.e., explained variance plotted as a function of the number of clusters).

Assumption testing revealed a violation of Levene's homogeneity of variances test, therefore, Welch's One-Way ANOVAs were conducted on participants' z-scores to compare cluster-level performance across the 66 relevant performance measures, and Games-Howell post-hoc comparisons were used to tease apart statistically significant relationships. Quantization error (i.e., how accurately the output data represents the input data), topographic error (i.e., how accurately the model preserves the topology of the input data), and Kaski-Lagus error (i.e., how accurately the model to preserves the underlying structure of the input data) were calculated to assess the accuracy of the SOM model, and individual cognitive profiles assigned by the clustering algorithm were compared with the formal diagnostic status of participants.

Results

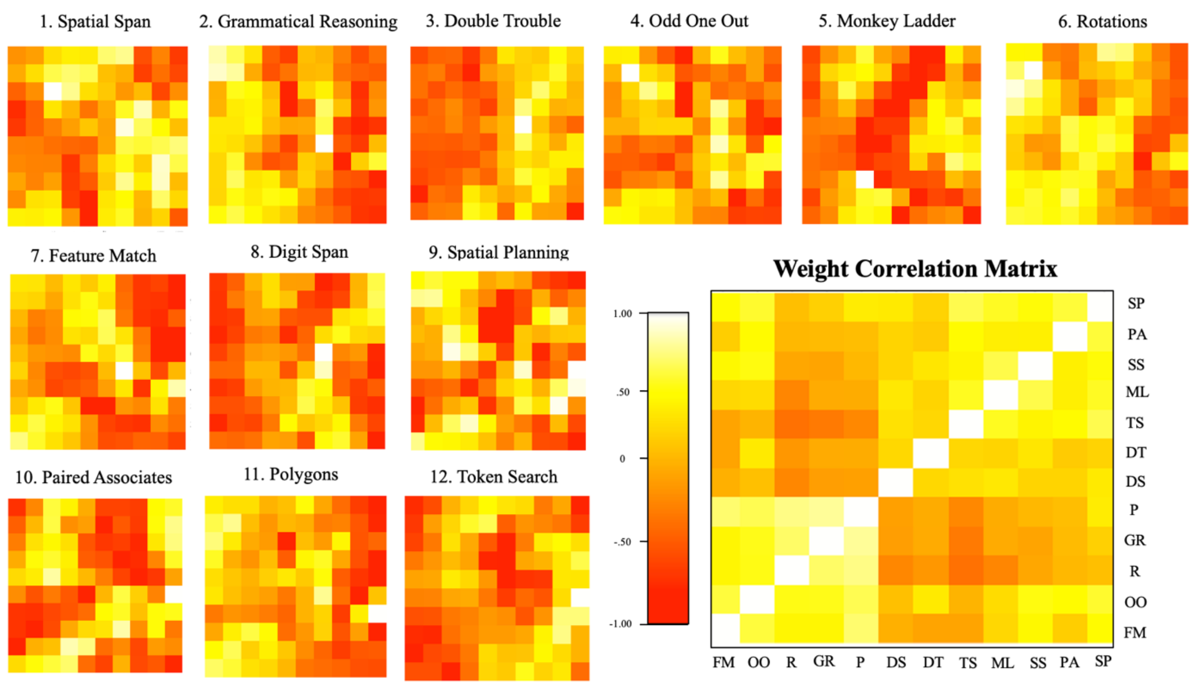
Comparison of the Weight Matrices:

The similar node weight topographies for each weight vector (i.e., the weights corresponding to each cognitive task across the grid of nodes) shown in Figure 1 indicate that the cognitive tasks discriminate between participants in similar way. For example, high weights tend to cluster along the left side of the topographical maps for Digit Span, Token Search, and Double Trouble, whereas low weights tend to cluster along the left side of the topographical maps for Grammatical Reasoning, Feature Match, Polygons, and Rotations.

This observation is further substantiated by the weight correlation matrix, which demonstrates an average inter-item correlation of $r = 0.38$, ranging from $r = -0.21$ to $r = 0.80$. In accordance with previous research, the cognitive tasks appear to group together according to the higher-order cognitive domain being measured, such that Grammatical Reasoning, Feature Match, Polygons, and Rotations are highly inter-correlated ($r = 0.64$), Monkey Ladder, Spatial Span, Paired Associates, Spatial Planning, and Odd One Out are highly intercorrelated ($r = 0.50$), and Digit Span, Token Search, and Double Trouble are moderately intercorrelated ($r = 0.28$). These findings correspond with Hampshire and colleagues' (2012) proposed factor structure of the testing battery, derived from a principal component analysis with orthogonal rotation that identified three overarching cognitive domains, including reasoning, short-term memory, and verbal ability. For example, there are high factor loadings for Grammatical Reasoning (0.33), Feature Match (0.57), Polygons (0.54), and Rotations (0.66) onto the reasoning domain. Similar observations were noted for Monkey Ladder (0.69), Spatial Span (0.69), Paired Associates (0.58), Spatial Planning (0.41), and Odd One Out (0.19) onto the short-term memory domain, and for Digit Span (0.71), Token Search (0.16), and Double Trouble (0.51) onto the verbal ability domain. These findings suggest that the SOM represents the cognitive data well, accounting for 64% of total variance, which corresponds with expected results based on the literature. Quality measures associated with the SOM indicate that the model is highly robust, with a quantization error of 10.35, topographic error of 0.65, and Kaski-Lagus error of 7.95.

Figure 1

Pearson Correlation Matrix and Weight Distributions from Self-Organizing Map, Split by Task



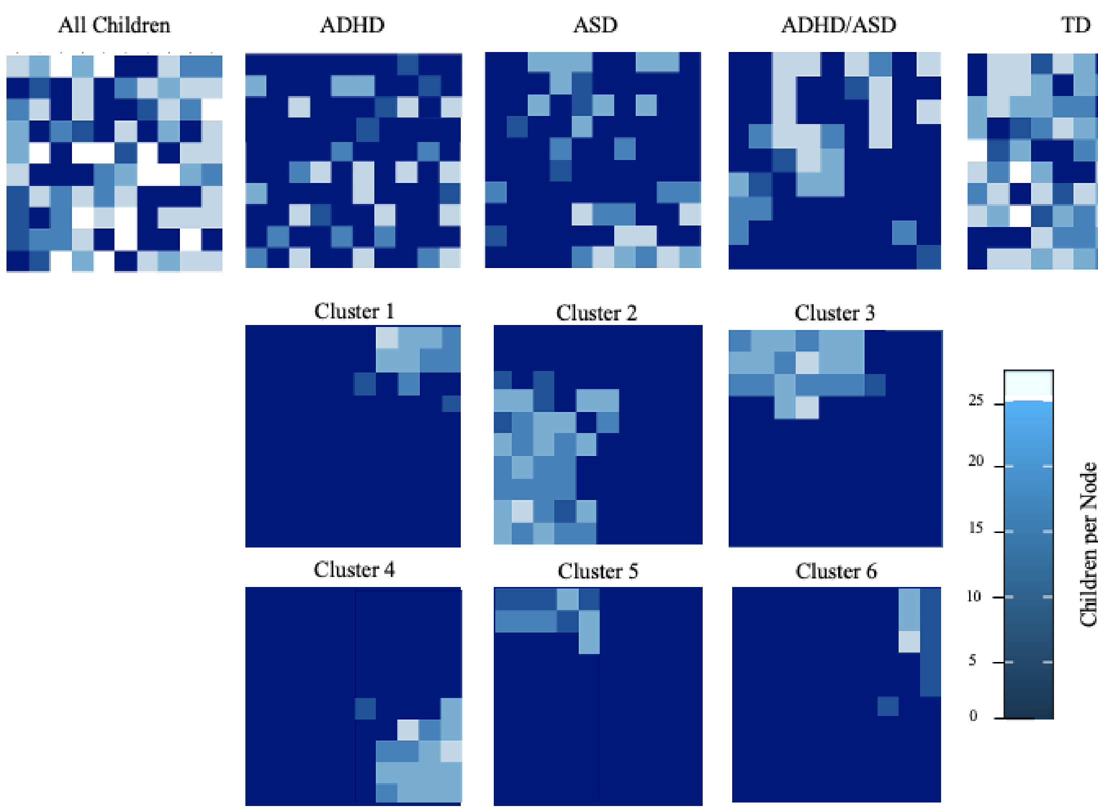
Note. The map depicts high weights (i.e., good performance) as yellow squares and low weights (i.e., poor performance) as red squares for each task. Pearson correlations between the weight distributions of tasks (i.e., inter-item correlations) are pictured in the bottom-right matrix.

Exploring Distributions of Different Categories of Children and Adolescents:

To determine whether participants' NDD diagnoses were reflected in the map, the distributions of children's best matching unit (BMU) were plotted for all children and then for children categorized by diagnosis in Figure 2. The topographical mappings demonstrate that category membership did not significantly predict cognitive profile, because participants from the same diagnostic groups did not collate together on the map. Rather, the best matching nodes were evenly scattered across the map, indicating that diagnostic status did not provide valuable insight into the cognitive profiles associated with different groups of children and adolescents.

Figure 2

The Distributions of Children and Adolescents' Best Matching Unit (BMU) Within the Map



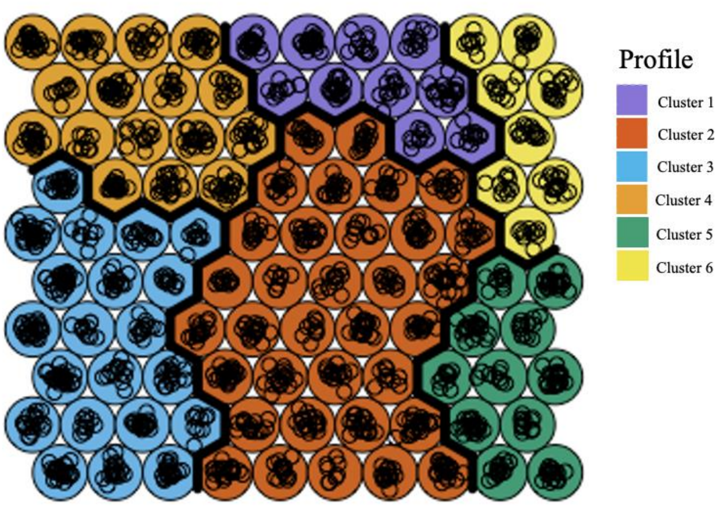
Note. The top panel shows the distributions of children's best matching unit (BMU) for all children and then for children categorized by diagnosis. The bottom panels show the distributions of children assigned to each of the six clusters.

Identifying Cognitive Profiles:

Figure 3 depicts the six cognitive profiles that emerged from the analysis, including: cluster one, which consisted of disengaged performers; cluster two, which comprised highly accurate performers in measures of selective attention and deductive reasoning; cluster three, which consisted of highly accurate performers across all measures; cluster four which included average performers with delays in episodic memory; cluster five which consisted of average performers with strengths in spatial manipulation and working memory, and cluster six, which contained impulsive performers (see Table 1). Means, standard deviations, and one-way analyses of variance can be found on Table 2, an overview of the cognitive profiles on Table 3. Figure 4 demonstrates that diagnostic status did not correspond with cluster membership.

Figure 3

Self-Organizing Map Topography



Note. The SOM of size 10x10 with a hexagonal topology and a bubble neighbourhood function was trained using 1529 observations, 200 iterations, and learning rate of $\alpha = 0.05$. The distance measure used is sum of squares, and mean distance to the closest unit in the map is 4.007.

Table 1

Demographic Characteristics of Participants, Split by Cluster Membership

Characteristic	Cluster 1		Cluster 2		Cluster 3		Cluster 4		Cluster 5		Cluster 6	
	n	*%*	*n*	*%*	*n*	*%*	*n*	*%*	*n*	*%*	*n*	*%*
N	103	6.7	434	28.4	377	24.7	291	19	231	15.1	93	6.1
Gender												
Male	67	65.0	293	67.5	245	65.0	204	70.1	151	65.4	64	68.8
Female	36	35.0	141	32.4	132	35.0	87	29.9	80	34.6	29	31.2
Diagnosis												
ADHD	36	35.0	132	30.4	113	30.0	116	39.9	81	35.1	32	34.4
ASD	3	2.9	10	2.3	7	1.9	8	2.7	6	2.46	8	8.6
ADHD/ASD	3	2.9	9	2.1	4	1.1	11	3.7	7	3.0	8	8.6
N/A	61	59.2	283	65.2	253	67.1	156	53.6	137	59.3	45	52.7

Note. $N = 1529$. Participants were on average 10.60 years old, ($SD = 2.69$), and participant age did not differ significantly by diagnosis.

Table 2

Means, Standard Deviations, and One-Way Analyses of Variance in Cognitive Assessments

Measure	Cluster 1		Cluster 2		Cluster 3		Cluster 4		Cluster 5		Cluster 6		*F*
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	
Spatial Span													
Max score	-0.55	0.88	0.26	0.76	0.49	0.83	-0.53	0.91	0.15	0.76	**-1.33**	1.36	80.1***
Avg score	-0.49	0.88	0.26	0.70	0.48	0.76	-0.50	1.00	0.14	0.67	-1.42	1.53	71.5***
Avg ms/item	0.10	0.29	-0.03	0.10	-0.07	0.11	-0.01	0.13	-0.06	0.09	0.49	4.01	16.1***
Num correct	-0.63	0.83	0.27	0.87	0.46	0.91	-0.54	0.83	0.11	0.90	-1.03	1.00	84.1***
Num attempt	-0.63	0.83	0.27	0.87	0.46	0.91	-0.54	0.83	0.11	0.90	-1.03	1.00	84.1***
Grammatical Reasoning													
Final score	-0.32	0.71	0.12	0.82	**0.68**	0.98	-0.56	0.84	-0.21	0.91	**-0.72**	0.98	80.0***
Num errors	-0.41	0.54	-0.37	0.63	-0.33	0.70	0.16	0.94	0.57	1.10	1.62	1.33	78.0***
Num correct	-0.79	0.79	-0.20	0.74	0.53	0.92	-0.53	0.77	0.28	0.99	0.65	1.40	82.7***
Num attempt	**-0.78**	0.65	-0.37	0.60	0.14	0.71	-0.25	0.86	0.54	1.12	**1.45**	1.57	80.2***
Double Trouble													
Final Score	-0.25	0.58	0.32	0.86	**0.39**	1.25	-0.39	0.70	-0.34	0.85	-0.73	0.76	60.3***

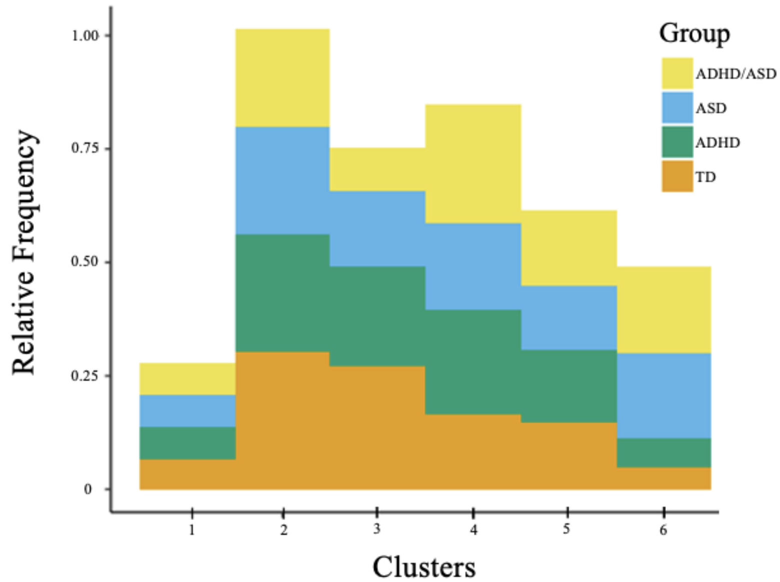
PCT_CC	0.10	1.15	**0.34**	0.73	0.12	0.86	-0.14	1.04	-0.32	1.06	-0.94	1.24	33.4***
PCT_CI	0.11	0.97	0.23	0.97	0.07	1.06	-0.27	1.02	-0.13	0.90	-0.29	0.78	12.9***
PCT_IC	-0.14	1.10	0.23	1.02	0.21	0.97	-0.20	0.96	-0.26	0.89	-0.45	0.82	20.0***
PCT_II	0.03	1.06	0.31	0.93	0.22	1.07	-0.34	0.89	-0.37	0.88	-0.38	0.83	32.9***
RT_CC	1.63	2.46	0.20	0.62	-0.20	0.58	-0.08	0.71	-0.43	0.49	-0.59	0.59	65.0***
RT_CI	1.66	1.63	0.34	0.82	-0.29	0.64	-0.11	0.76	-0.50	0.74	-0.68	0.77	78.7***
RT_IC	1.27	1.51	0.33	0.86	-0.23	0.75	-0.05	0.84	-0.46	0.85	-0.69	0.84	57.7***
RT_II	1.67	1.96	0.32	0.80	-0.28	0.57	-0.15	0.65	-0.46	0.65	-0.69	0,78	69.6***
Num errors	-0.70	0.36	-0.52	0.51	-0.05	0.95	-0.46	0.69	-0.46	1.16	-0.65	1.45	125.9***
Num correct	-1.10	0.53	-0.22	0.67	0.40	0.92	-0.27	0.73	0.34	1.11	0.60	1.69	108.0***
Num attempt	**-1.06**	0.36	-0.46	0.41	0.20	0.76	-0.04	0.71	0.60	1.25	1.14	1.80	174.2***
Odd One Out													
Final score	0.30	0.64	**0.32**	0.63	0.31	0.57	0.02	0.70	-0.29	0.83	**-2.42**	1.60	75.3***
Max score	-0.76	1.19	0.07	0.84	0.51	0.80	-0.27	0.87	0.20	0.81	-1.20	1.25	60.9***
Num errors	-0.62	0.48	0.33	0.62	-0.17	0.55	-0.12	0.68	0.40	0.87	2.30	1.76	79.5***
Num correct	-0.71	1.18	0.07	0.82	0.51	0.82	-0.27	0.85	0.18	0.83	-1.24	1.26	60.4***
Num attempt	**-0.90**	0.59	-0.31	0.68	0.03	0.62	-0.22	0.70	0.47	0.90	**1.85**	1.82	89.4***
Monkey Ladder													
Max score	-0.51	0.65	0.17	0.72	**0.72**	0.82	-0.61	0.96	-0.08	0.85	-1.05	1.19	75.3***
Avg. score	-0.56	0.68	0.18	0.69	0.72	0.79	-0.61	0.96	-0.08	0.84	-1.06	1.27	60.9***
Avg. ms/item	**0.84**	1.19	0.03	0.95	-0.38	0.75	0.22	1.06	-0.26	0.80	0.41	1.24	79.5***
Num correct	-0.48	0.68	0.19	0.72	0.69	0.80	-0.57	1.00	-0.13	0.85	-1.03	1.26	60.4***
Num attempts	-0.48	0.68	0.19	0.72	0.69	0.80	-0.57	1.00	-0.13	0.85	-1.03	1.26	89.4***
Rotations													
Final score	-0.36	0.65	0.04	0.74	**0.60**	0.95	-0.45	0.82	0.12	1.22	**-1.08**	0.76	89.6***
Max score	-0.53	0.79	0.04	0.76	0.56	0.91	-0.48	0.92	0.32	1.12	-0.79	0.88	71.3***
Correct score	-0.70	0.66	-0.29	0.66	0.39	0.96	-0.44	0.80	0.80	1.11	-0.05	1.18	83.0***
Num errors	-0.39	0.55	-0.44	0.58	-0.39	0.63	0.11	0.84	0.77	1.12	1.79	1.13	123.2***
Num correct	-0.81	0.68	-0.40	0.66	0.16	0.83	-0.36	0.83	1.02	0.92	0.72	1.30	129.8***
Num attempts	**-0.67**	0.56	-0.49	0.57	-0.16	0.69	-0.12	0.81	1.02	1.01	**1.50**	1.23	140.5***
Feature Match													
Final score	-0.60	0.77	0.16	0.82	**0.70**	0.86	-0.43	0.80	-0.11	0.84	**-1.29**	1.06	110.1***
Max score	-0.74	0.93	0.16	0.75	0.68	0.71	-0.42	0.86	-0.01	0.87	-1.32	1.34	108.8***
Correct score	-0.89	0.85	0.03	0.79	0.71	0.81	-0.55	0.82	0.18	0.92	-0.74	1.18	114.3***
Num errors	-0.24	0.62	-0.29	0.55	-0.22	0.59	-0.10	0.68	0.41	1.05	1.85	2.12	36.2***
Num correct	-1.00	1.02	-0.04	0.75	0.61	0.72	-0.56	0.88	0.30	0.91	-0.19	1.51	99.2***
Num attempts	**-0.82**	0.84	-0.22	0.64	0.25	0.76	-0.44	1.07	0.47	1.07	1.10	1.98	70.6***
Digit Span													
Max score	-0.27	0.91	0.15	0.75	**0.53**	0.67	-0.56	1.13	0.15	0.84	**-1.15**	1.37	72.2***
Avg. score	-0.24	0.95	0.16	0.67	0.49	0.59	-0.55	1.22	0.17	0.82	-1.20	1.39	63.5***
Avg. ms/item	**1.02**	1.77	0.07	0.88	-0.45	0.61	0.22	0.88	-0.33	0.68	0.49	1.31	49.7***
Num correct	-0.29	0.94	0.05	0.90	0.89	0.78	-0.53	0.96	0.13	0.93	-0.94	0.97	78.9***
Num attempts	-0.29	0.94	0.05	0.90	0.89	0.78	-0.53	0.96	0.13	0.93	-0.94	0.97	78.9***
Spatial Planning													

Final score	-0.23	0.71	0.13	0.80	**0.61**	1.07	-0.44	0.79	-0.27	0.93	-0.82	1.04	61.8***
Num errors	-0.70	0.76	-0.01	0.91	0.22	0.96	-0.13	0.96	0.19	1.09	-0.12	1.24	23.7***
Num correct	-0.18	0.76	0.12	0.79	0.60	0.93	-0.39	0.86	-0.25	1.03	-0.94	1.16	60.7***
Num attempts	-0.59	0.72	0.11	0.74	0.72	0.81	-0.47	0.86	-0.13	1.01	-1.00	1.22	104.1***
Paired Associates													
Max score	-0.54	0.69	-0.05	0.85	**0.66**	0.89	-0.37	1.02	0.08	0.86	**-0.95**	0.94	80.4***
Avg. score	-0.57	0.71	-0.02	0.85	0.65	0.88	-0.38	1.05	0.10	0.79	-0.98	0.98	81.2***
Avg. ms/item	0.09	0.19	-0.03	0.12	-0.08	0.10	**0.15**	2.27	-0.06	0.10	0.05	0.18	27.2***
Num correct	-0.46	0.76	-0.06	0.88	0.63	0.86	-0.30	1.04	0.06	0.81	-1.00	1.03	71.7***
Num attempts	-0.46	0.76	-0.06	0.88	0.63	0.86	-0.30	1.04	0.06	0.81	-1.00	1.03	71.7***
Polygons													
Final score	-0.32	0.67	0.11	0.88	**0.50**	1.12	-0.39	0.78	-0.13	0.96	**-0.64**	0.98	41.6***
Num errors	-0.54	0.58	-0.38	0.62	-0.08	0.82	-0.07	0.78	0.42	0.91	1.84	1.67	65.2***
Num correct	-0.86	0.80	-0.17	0.78	0.50	0.85	-0.53	0.80	0.29	0.87	0.66	1.65	86.4***
Num attempts	**-0.89**	0.66	-0.34	0.65	0.27	0.76	-0.38	0.70	0.45	0.83	**1.55**	1.86	101.2***
Token Search													
Max score	-0.39	0.76	0.19	0.79	**0.72**	0.77	-0.41	0.87	-0.21	0.79	**-1.52**	1.07	128.1***
Avg. score	-0.30	0.78	0.21	0.77	0.68	0.67	-0.40	0.89	-0.22	0.81	-1.59	1.28	116.9***
Avg. ms/item	**1.13**	1.48	0.16	1.01	-0.32	0.62	0.10	0.89	**-0.46**	0.59	0.11	1.36	46.6***
Num correct	-0.42	0.83	0.18	0.81	0.73	0.79	-0.46	0.91	-0.19	0.78	-1.41	0.88	136.7***
Num attempts	-0.42	0.83	0.19	0.81	0.72	0.80	-0.47	0.91	-0.19	0.78	-1.40	0.86	138.7***

Note. Bold mean scores indicate relevant performance measures that distinguished between the clusters. RT_CC = reaction time (congruent-congruent trial), RT_CI = reaction time (congruent-incongruent trial), RT_IC = reaction time (incongruent-congruent trial), RT_II = reaction time (incongruent-incongruent trial). PCT_CC = percent correct (congruent-congruent trial), PCT_CI = percent correct (congruent-incongruent trial), PCT_IC = percent correct (incongruent-congruent trial), PCT_II = percent correct (incongruent-incongruent trial). *** $p < .001$

Figure 4

Relative Frequency of Cluster Membership



Note. Absolute frequency has been statistically adjusted (100% of cases divided by six clusters) to show the relative proportion of each diagnostic group across the clusters.

Table 3

Overview of Cognitive Profiles

Cluster	Description
1	• Least number of attempts: ○ Verbal memory ability $F(5, 427) = 80.2$, $p < .001$, $M = -0.78$, $SD = 0.65$ ○ Selective attention and processing speed $F(5, 436) = 174.2$, $p < .001$, $M = -1.06$, $SD = 0.36$ ○ Spatial manipulation $F(5, 433) = 140.5$, $p < .001$, $M = -0.67$, $SD = 0.56$ ○ Attentional processing $F(5, 421) = 70.6$, $p < .001$, $M = -0.82$, $SD = 0.84$ ○ Visuospatial processing $F(5, 432) = 101.2$, $p < .001$, $M = -0.88$, $SD = 0.66$ ○ Deductive reasoning $F(5, 433) = 89.4$, $p < .001$, $M = -0.90$, $SD = 0.59$. • Longest response times: ○ Visuospatial working memory $F(5, 430) = 34.5$, $p < .001$, $M = 0.84$, $SD = 1.19$ ○ Verbal working memory ($F(5, 422) = 49.7$, $p < .001$, $M = 1.02$, $SD = 1.77$ ○ Working memory and strategy $F(5, 426) = 46.6$, $p < .001$, $M = 1.13$, $SD = 1.48$

2	• Highest percent of correct responses:	
		○ Selective attention and processing speed $F(5, 425) = 33.4$, $p < .001$, $M = 0.35$, $SD = 0.73$
	• Highest final score:	
		○ Deductive reasoning $F(5, 428) = 75.3$, $p < .001$, $M = 0.31$, $SD = 0.57$
3	• Highest final score:	
		○ Verbal memory ability $F(5, 448) = 80.0$, $p < .001$, $M = 0.68$, $SD = 0.97$
		○ Selective attention and processing speed $F(5, 466) = 60.3$, $p < .001$, $M = 0.39$, $SD = 1.25$
		○ Visuospatial working memory $F(5, 441) = 110.4$, $p < .001$, $M = 0.72$, $SD = 0.82$
		○ Spatial manipulation $F(5, 453) = 89.6$, $p < .001$, $M = 0.56$, $SD = 0.91$
		○ Attentional processing $F(5, 442) = 110.1$, $p < .001$, $M = 0.70$, $SD = 0.86$
		○ Verbal working memory $F(5, 427) = 72.2$, $p < .001$, $M = 0.53$, $SD = 0.67$
		○ Executive functioning $F(5, 447) = 61.8$, $p < .001$, $M = 0.62$, $SD = 1.07$
		○ Episodic memory $F(5, 451) = 80.4$, $p < .001$, $M = 0.66$, $SD = 0.89$
		○ Visuospatial processing $F(5, 454) = 41.6$, $p < .001$, $M = 0.50$, $SD = 1.12$
		○ Working memory and strategy $F(5, 440) = 128.1$, $p < .001$, $M = 0.72$, $SD = 0.77$
4	• Slowest response time:	
		○ Episodic memory $F(5, 424) = 27.2$, $p < .001$, $M = 0.14$, $SD = 2.27$
5	• Highest number of correct responses:	
		○ Spatial manipulation $F(5, 434) = 129.8$, $p < .001$, $M = 1.02$, $SD = 0.92$
	• Fastest response time:	
		○ Working memory and strategy $F(5, 426) = 46.6$, $p < .001$, $M = -0.46$, $SD = 0.59$
6	• Highest number of attempts:	
		○ Verbal memory ability $F(5, 427) = 80.2$, $p < .001$, $M = 1.45$, $SD = 1.57$
		○ Deductive reasoning $F(5, 433) = 89.4$, $p < .001$, $M = 1.85$, $SD = 1.82$
		○ Spatial manipulation $F(5, 422) = 140.5$, $p < .001$, $M = 1.50$, $SD = 1.23$
		○ Visuospatial processing $F(5, 432) = 101.2$, $p < .001$, $M = 1.55$, $SD = 1.86$
	• Lowest final scores:	
		○ Short-term memory $F(5, 433) = 80.1$, $p < .001$, $M = -1.33$, $SD = 1.36$
		○ Verbal memory ability $F(5, 448) = 80.0$, $p < .001$, $M = -0.72$, $SD = 0.98$
		○ Deductive reasoning $F(5, 428) = 75.3$, $p < .001$, $M = -2.43$, $SD = 1.60$
		○ Spatial manipulation $F(5, 453) = 89.6$, $p < .001$, $M = -0.63$, $SD = 0.98$
		○ Attentional processing $F(5, 442) = 110.1$, $p < .001$, $M = -1.29$, $SD = 10.6$
		○ Verbal working memory $F(5, 427) = 72.2$, $p < .001$, $M = -1.15$, $SD = 1.27$
		○ Executive functioning $F(5, 447) = 61.8$, $p < .001$, $M = -0.82$, $SD = 1.04$
		○ Episodic memory $F(5, 451) = 80.4$, $p < .001$, $M = -0.95$, $SD = 0.94$
		○ Visuospatial processing $F(5, 454) = 41.6$, $p < .001$, $M = -0.64$, $SD = 0.98$
		○ Working memory and strategy $F(5, 440) = 128.1$, $p < .001$, $M = -1.53$, $SD = 1.07$

Note. Assumption testing revealed a violation of Levene's homogeneity of variance test, warranting the use of Welch's ANOVAs and Games-Howell post-hoc comparisons.

Discussion

The present study identified six cognitive profiles from a large heterogenous sample of children and adolescents with NDDs, including disengaged performers, highly accurate performers in measures of selective attention and deductive reasoning, highly accurate performers across all cognitive measures, average performers with weaknesses in episodic memory, average performers with strengths in spatial manipulation and working memory, and impulsive performers. The variability observed in cognitive performance across participants in the sample reflects the extent to which heterogeneity characterizes disorders of childhood. Additionally, diagnostic status of participants did not correspond with cluster membership, providing evidence for the application of transdiagnostic approaches toward understanding neurodiversity in developmental populations.

These results correspond with findings previously established in the literature by Astle and colleagues (2019), and Suigzdaite and colleagues (2020), whose research did not identify a relationship between participants' initial diagnoses and transdiagnostic cognitive profile. Furthermore, evidence of cognitive heterogeneity may account for inconsistent findings in the literature regarding the cognitive performance of children and adolescents with NDDs. Several meta-analytic studies such as those conducted by East-Richard and colleagues (2020) and Craig and colleagues (2016) have revealed contradictory findings in cognitive performance for individuals with ADHD, ASD, and comorbid ADHD/ASD in nearly every domain of cognitive functioning. For example, East-Richard and colleagues conducted a comprehensive review of 11 meta-analyses that incorporated 445 studies and reported large deficits in visuospatial working memory among individuals with ADHD (g = 1.14), whereas only moderate impairments were observed among those with ASD (g = 0.58). However, Craig and colleagues (2016) observed no significant differences in working memory performance between ADHD, ASD, and TD groups in their meta-analysis of a similar magnitude. Across both studies, cognitive heterogeneity in the participant sample may be responsible for these inconsistent findings.

Additionally, contrary to the executive dysfunction hypothesis of ADHD and ASD, which argues that ADHD is distinguished by deficits in response inhibition and working memory (Corbett et al., 2009: Willcutt et al., 2005), whereas ASD is distinguished by deficits in planning and flexibility (Hill, 2004; Sinzig et al., 2008), the present study did not find evidence to support the proposed double dissociation. Deficits in response inhibition and working memory, as measured by the Double Trouble and Token Search tasks, were identified in cluster one and cluster six, which both contained members with various diagnoses. Likewise, impairments in planning and flexibility, as measured by the Spatial Planning task, were observed in cluster six, which consisted of members with various diagnoses.

Given the significant gap in the literature with respect to the identification of cognitive profiles among individuals with comorbid ADHD/ASD, the present study helps to further elucidate the nature of the diagnosis. Although many researchers argue in favour of the Additivity Hypothesis (e.g., Colombi & Ghaazuiddin, 2017; Cooper et al., 2014; Craig et al., 2016; Goldstein et al., 2004; Lukito et al., 2017; Shepard et al., 2018; Sinzig et al., 2008; Tye et al., 2014; Yerys et al., 2009), which posits that separate but correlated risk factors lead to the co-occurrence of ADHD and ASD, producing an additive combination of deficits from two separate nosologies, the present study did not find evidence to support this theory. Rather, implementing a transdiagnostic approach revealed many discrepancies between participants' formal diagnostic status and actual cognitive performance, such that members from different diagnostic groups were observed in each of the cognitive profiles identified. This finding suggests that NDDs are best conceptualized in terms of multiple continuous dimensions along which individuals may be located. Traditional binarization between diagnostic groups does not adequately capture the cognitive heterogeneity observed within and across groups, as demonstrated by the absence of an additivity effect in comorbid ADHD/ASD.

Importantly, the cognitive deficits observed in TD participants may reflect the presence of undiagnosed learning difficulties, emphasizing the need for more accessible cognitive assessment tools in school-based settings. Considering that many school districts require students to obtain formal documentation before administering special education services, many children and adolescents may consequently be denied access to appropriate supports. Given that the inaccessibility of cognitive assessments is often amplified by systematic barriers (Constantino et al., 2020; Tek & Landa, 2012; Williams et al., 2022; Zuckerman et al., 2017), an absence of accessible assessment tools further contributes to systemic inequality perpetuated by race, ethnicity, gender, and socioeconomic status. To counteract these effects, school districts may consider introducing online cognitive assessments to help detect learning impairments.

Limitations of the Present Study:

There are several limitations associated with the present study. Firstly, although the participants included in the sample demonstrated extensive neurodiversity, they may not accurately represent the wider population of children and adolescents with NDDs because they were enrolled in the Brain Balance Program, a multimodal cognitive training program. As these individuals were seeking out services to help improve their cognitive performance, the sample may have only extended to capture those with the most severe learning difficulties that warrant intervention. Additionally, there are financial barriers to accessing the Brain Balance Program because of enrollment fees, meaning the sample may have been largely skewed towards families with higher socioeconomic statuses, thus presenting challenges for generalizability. However, variables such as age, biological sex, and socioeconomic status were statistically controlled for in preliminary analyses, thus reducing these effects as much as possible.

As with previous research, the continuous mapping process is not confined by clear boundaries, which makes the identification of unique clusters highly dependent on the parameters specified by investigators. Although the machine learning parameters were informed by visual examinations of the data with scree plots and the elbow method, the model only accounted for 64% of the total variance, yet caution was exercised to prevent over-fitting and the introduction of noise into the analysis.

Future Directions:

Given the robustness of the current unsupervised machine learning model, future investigations should explore whether converting it into a supervised machine learning model is appropriate for determining the cluster-membership of participants from additional data sets. Furthermore, a meta-analytic review of the literature may be used to inform the procurement of appropriate school-based supports to children and adolescents with NDDs according to their cognitive profiles. A strengths-based approach to intervention may be introduced by leveraging the cognitive strengths associated with each cluster profile to accommodate individual needs.

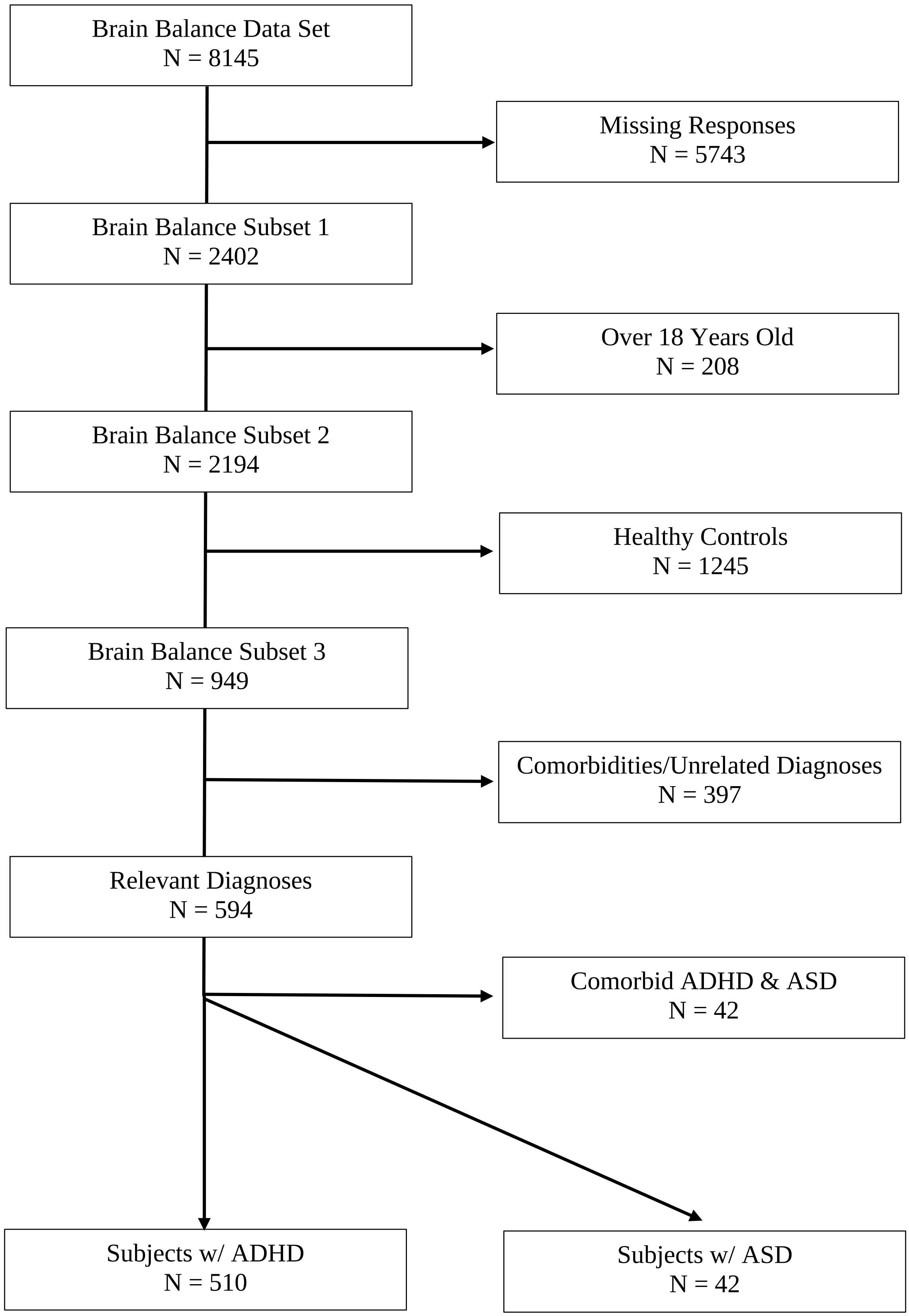
Practical Implications:

The findings from the present study indicate that *Creyos* cognitive assessments, although not established as a formal diagnostic tool, may provide valuable information about students' cognitive performance to practitioners by allowing for efficient, large-group administration. Such an approach may allow for the stratification of more comprehensive psychoeducational assessments towards students who demonstrated cognitive deficits. This may help to ensure that individuals who require special education services obtain appropriate documentation in a timely manner, thus enabling them to access appropriate interventions and perform at their best ability at school. Furthermore, the information obtained about students' cognitive performance may help address barriers in accessing educational interventions among those without a formal diagnosis by identifying their specific areas of weakness. These deficits may then be addressed by introducing informal educational interventions that are supported by research. For example, peer-tutoring and contingency management techniques may be used to promote engaged learning among those identified as 'disengaged performers' by the machine learning algorithm (DuPaul et al., 2014; Staff et al., 2021). Regardless of whether formal psychoeducational testing is pursued, the identification of children and adolescents' cognitive profiles may also provide helpful information to guide teachers when tailoring their support to students in the classroom.

Conclusion:

In summary, machine learning techniques were used to identify six cognitive profiles from a large heterogenous sample of children and adolescents with neurodevelopmental disorders using a 12-item web-based neurocognitive testing battery. Diagnostic status did not correspond with cluster-membership, providing evidence for the application of transdiagnostic approaches toward understanding cognitive heterogeneity in developmental populations. The cognitive deficits observed in typically-developing children also highlights the need for more assessable cognitive assessment tools in school-based settings to help detect undiagnosed learning difficulties. Ultimately, the transdiagnostic revolution represents substantial progress towards neurodiversity-informed developmental science that advocates for the depathologization of difference, and evidence bolstered by the present study may help to encourage a paradigm shift from traditional diagnostic nosologies to transdiagnostic approaches in research and clinical practice.

Appendix A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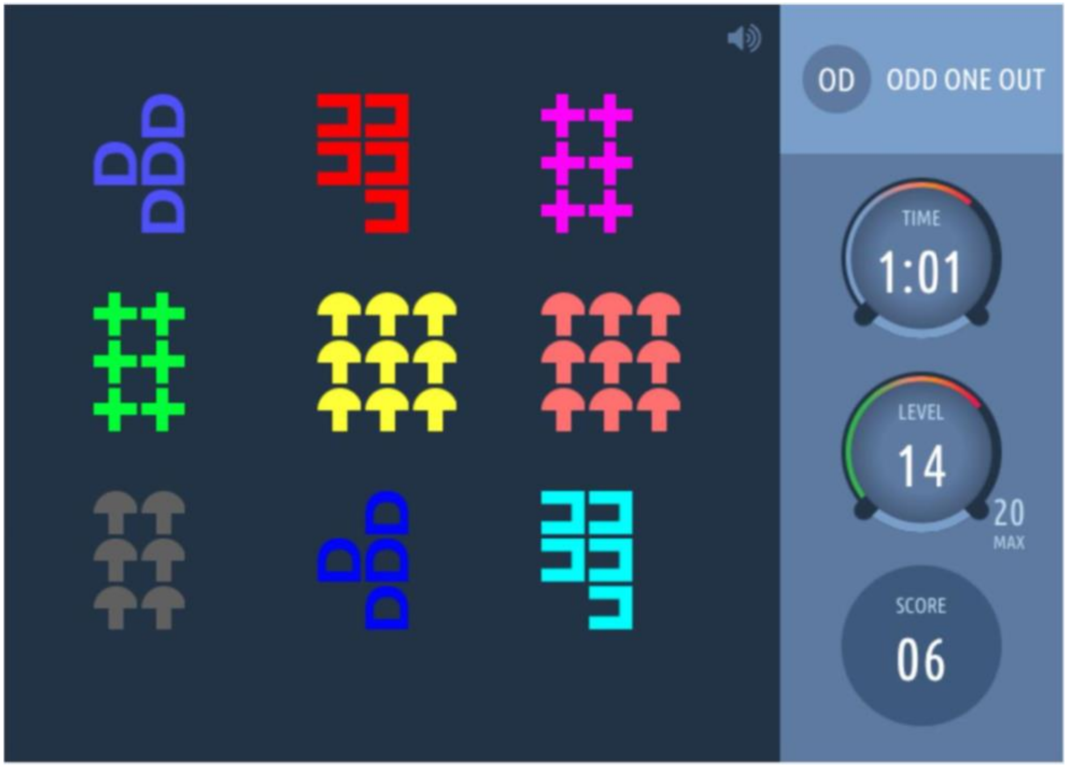
Missing Responses
N = 5743
Brain Balance Subset 1
N = 2402
Over 18 Years Old
N = 208
Brain Balance Subset 2
N = 2194
Healthy Controls
N = 1245
Brain Balance Subset 3
N = 949
Comorbidities/Unrelated Diagnoses
N = 397
Relevant Diagnoses
N = 594
Comorbid ADHD & ASD
N = 42
Subjects w/ ADHD
N = 510
Subjects w/ ASD
N = 42

Appendix B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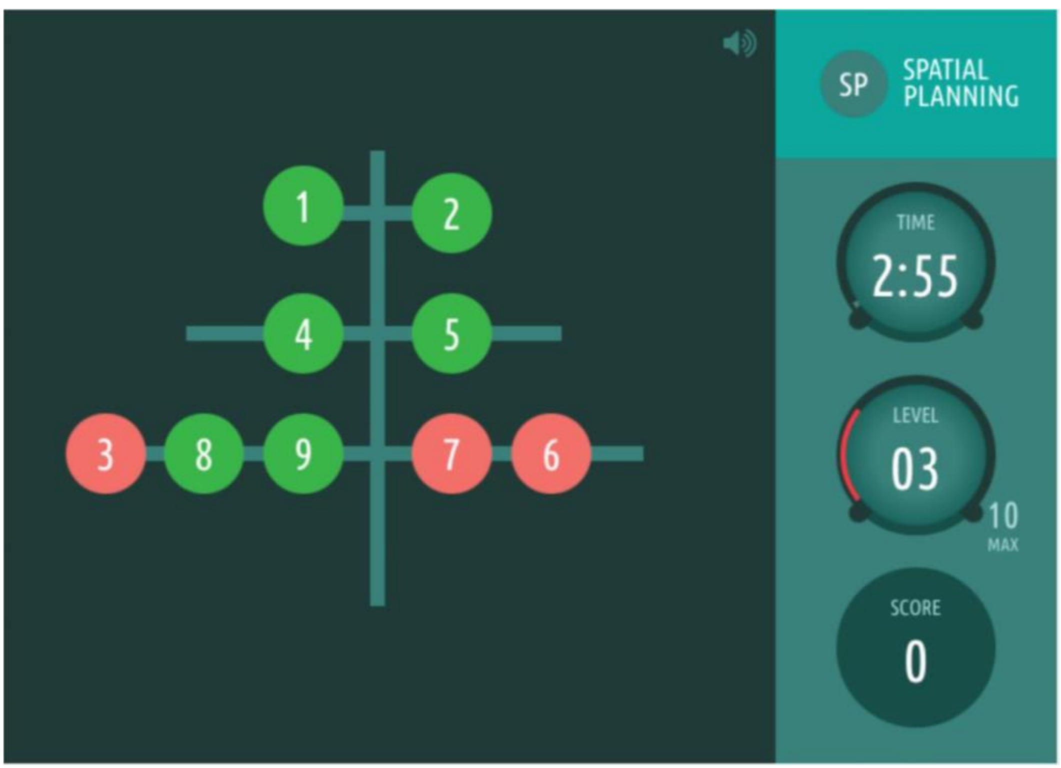
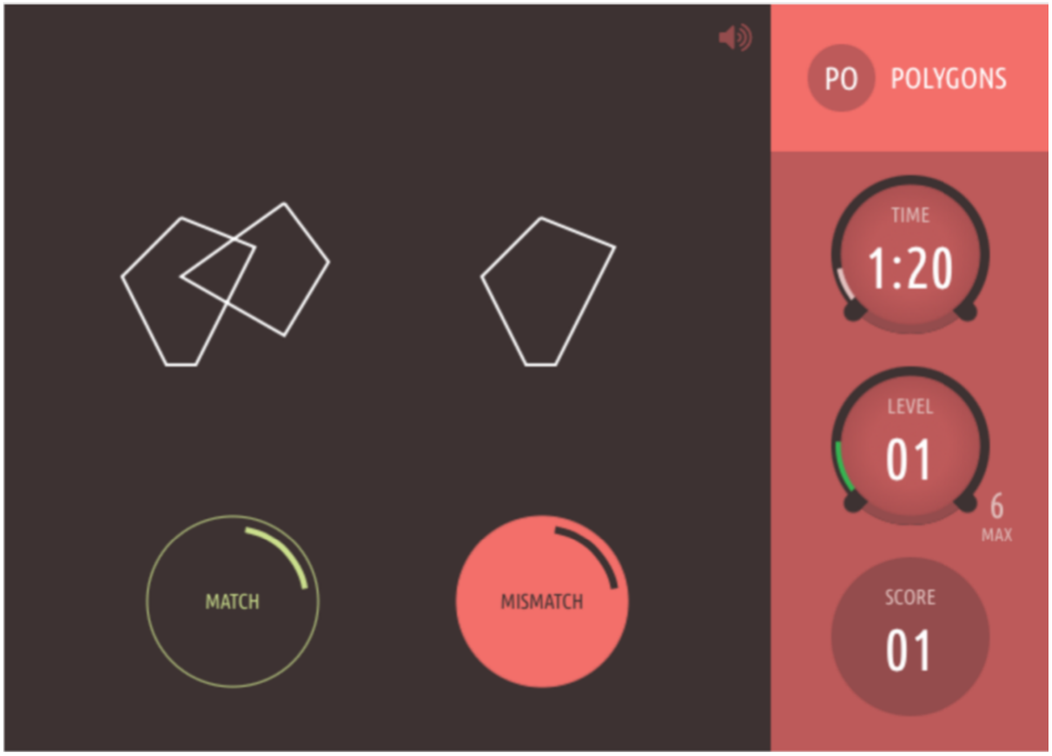
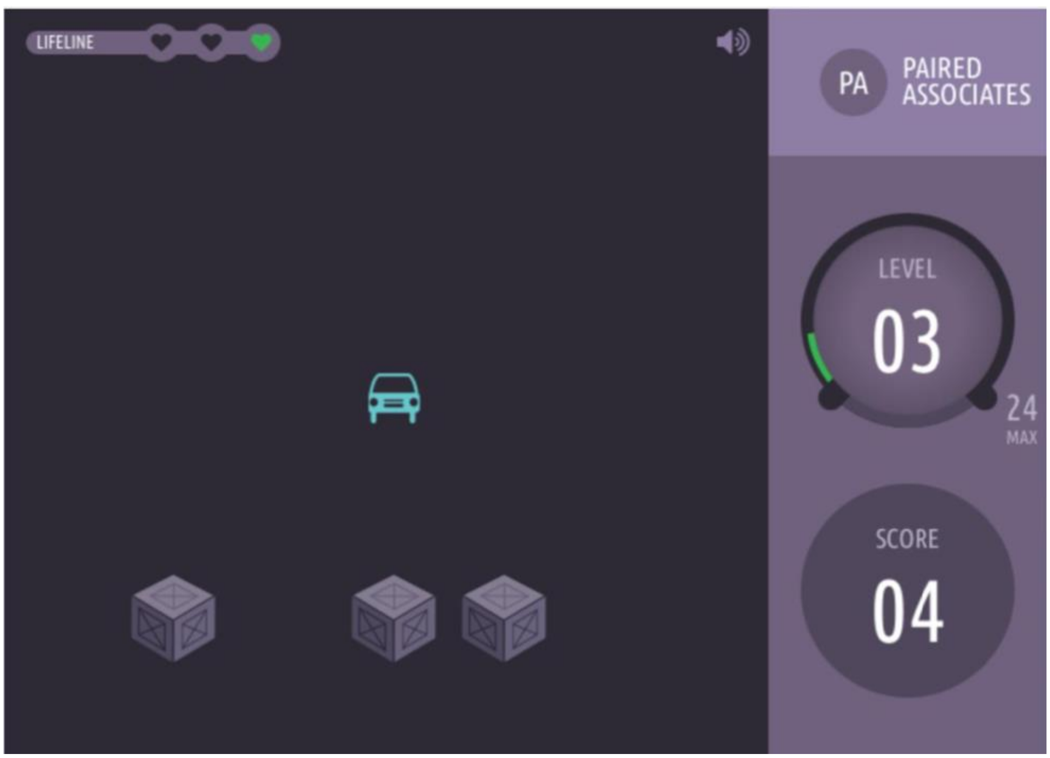
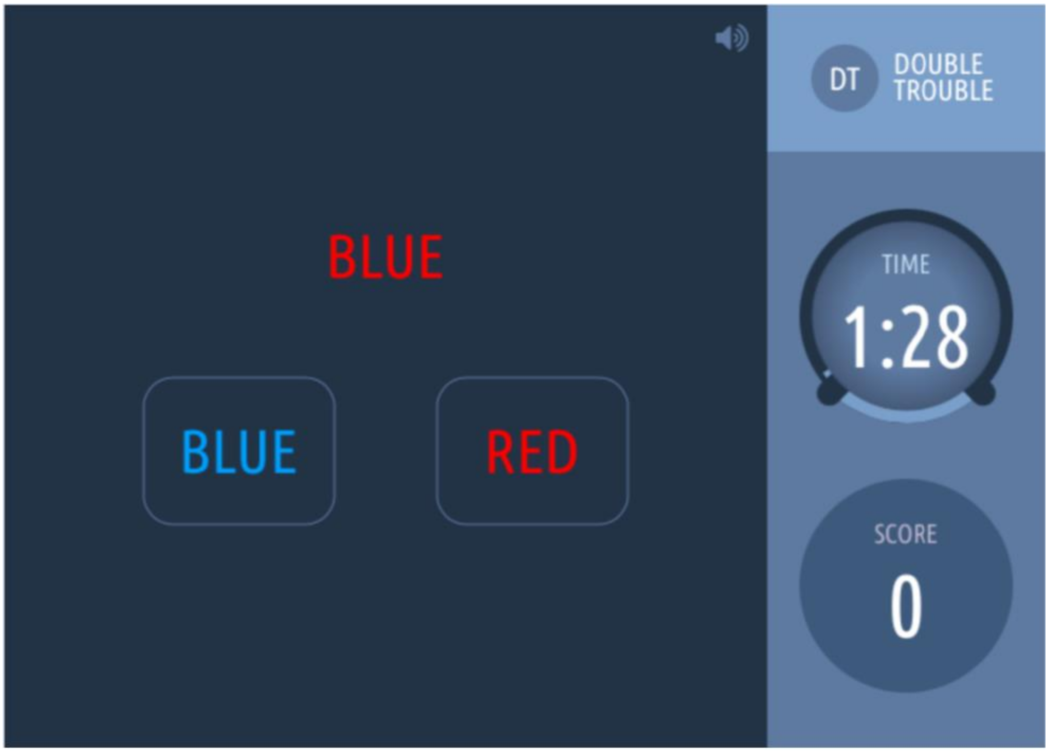
ODD ONE OUT
TIME
1:01
LEVEL
14
20
MAX
SCORE
06


SP
SPATIAL PLANNING
1
2
4
5
3
8
9
7
6
TIME
2:55
LEVEL
03
10
MAX
SCORE
0


PO POLYGONS
TIME
1:20
LEVEL
01
6
MAX
SCORE
01
MATCH
MISMATCH


LIFELINE
PA PAIRED ASSOCIATES
LEVEL
03
24
MAX
SCORE
04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DOUBLE TROUBLE
BLUE
BLUE
RED
TIME
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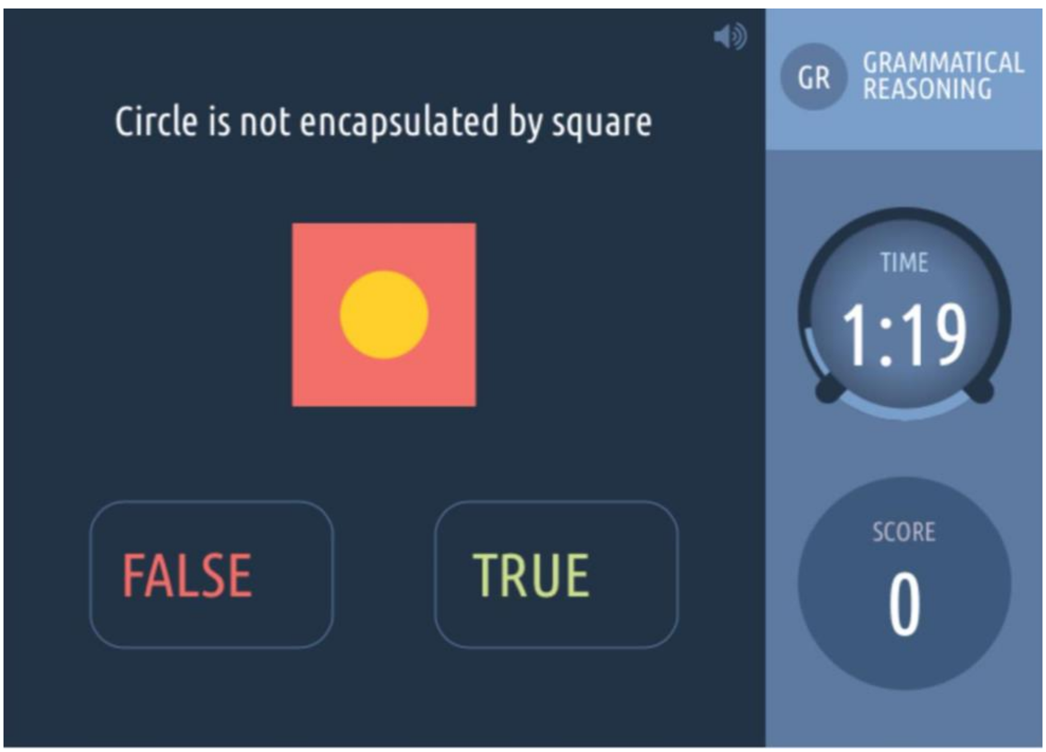
SCORE
0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GRAMMATICAL REASONING
Circle is not encapsulated by square
FALSE
TRUE
TIME
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SCORE
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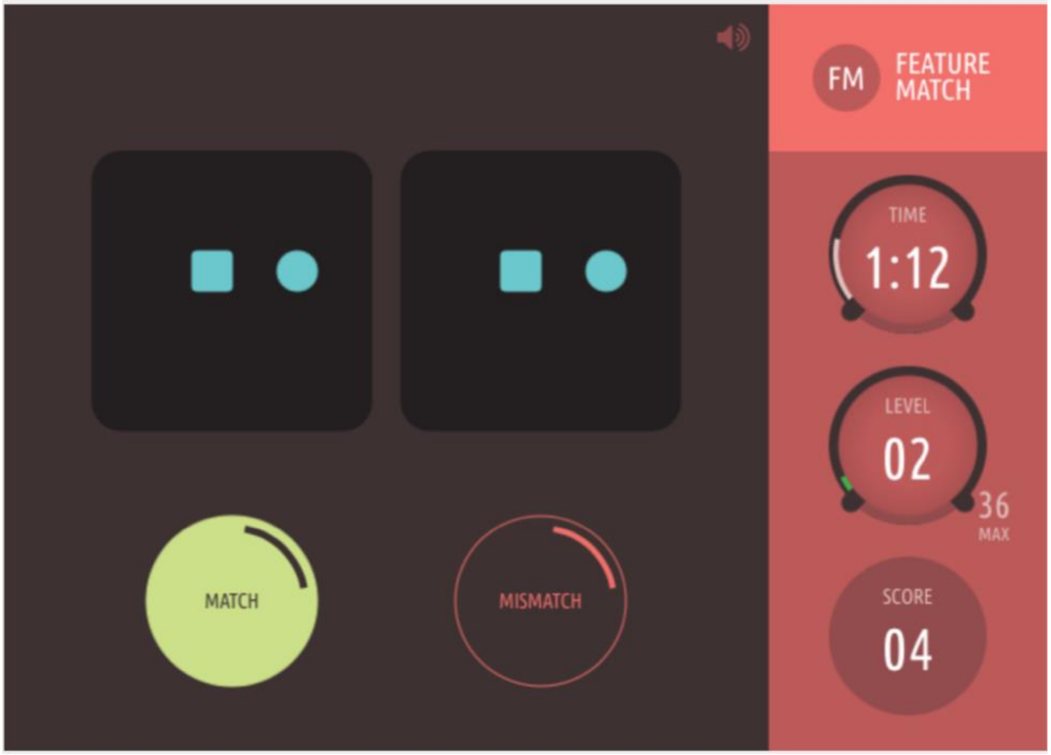
FM
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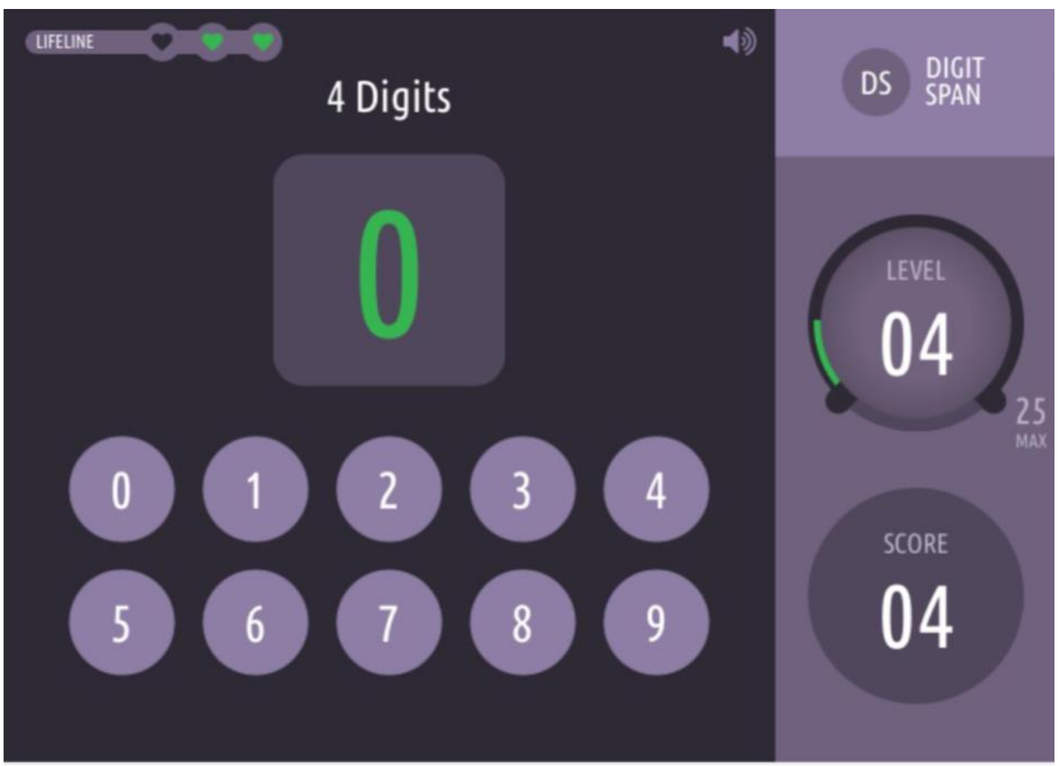
TIME
1:12
LEVEL
02
36
MAX
SCORE
04
MATCH
MISMATCH


LIFELINE
4 Digits
0
0 1 2 3 4
5 6 7 8 9
DS
DIGIT SPAN
LEVEL
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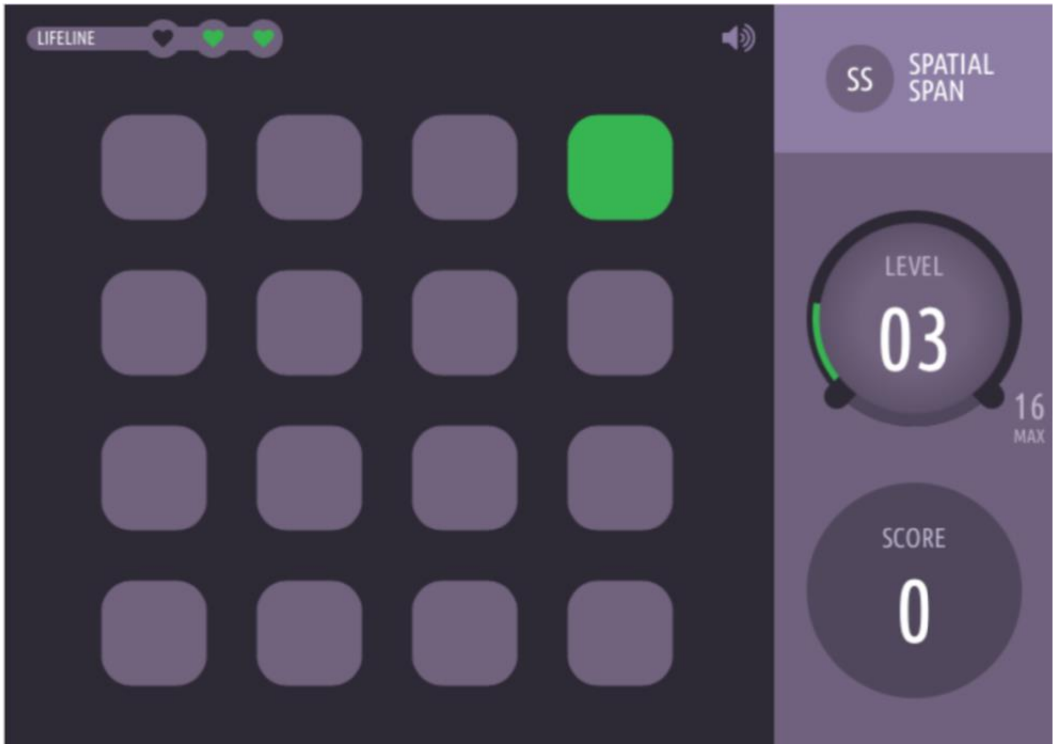
25
MAX
SCORE
04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SCORE
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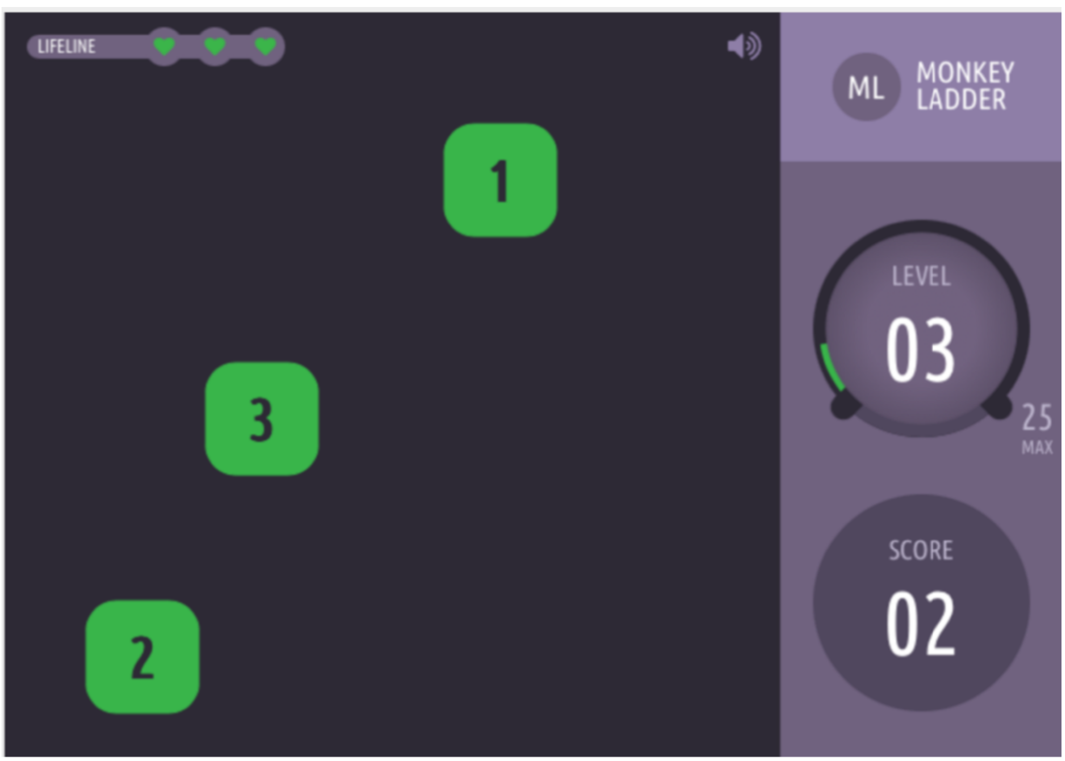
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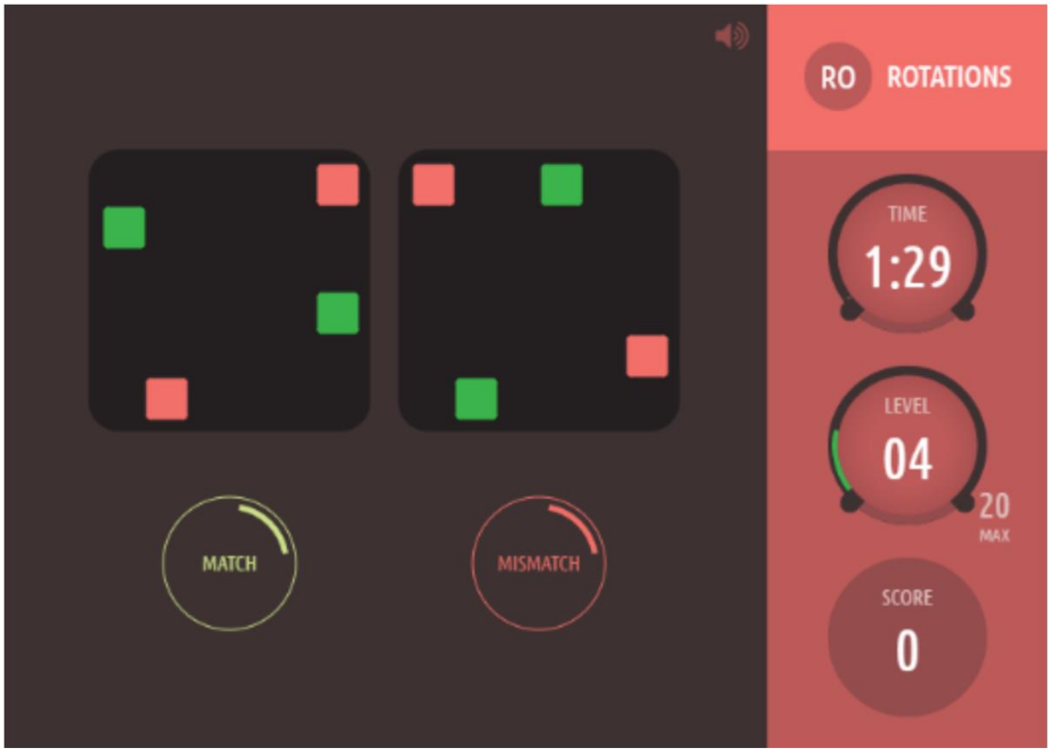
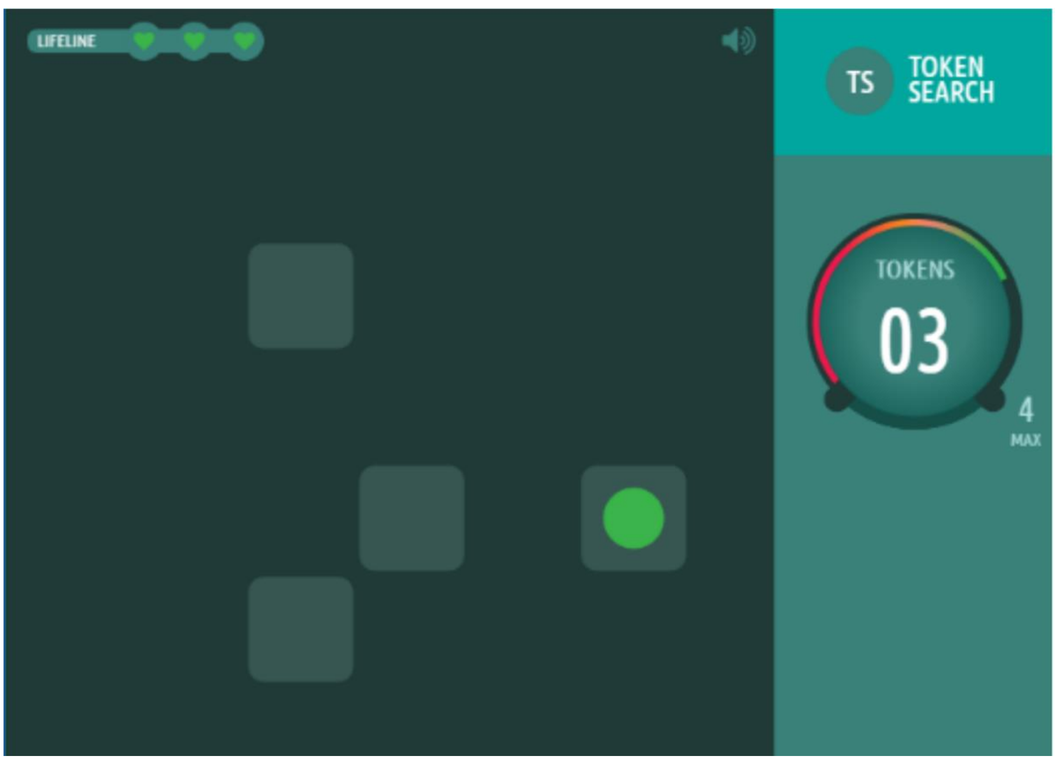
3
2
ML
MONKEY LADDER
LEVEL
03
25
MAX
SCORE
02


RO
ROTATIONS
TIME
1:29
LEVEL
04
20
MAX
SCORE
0
MATCH
MISMATCH


LIFELINE
TS
TOKEN
SEARCH
TOKENS
03
4
MAX

Appendix C

Questionnaire for Parents/Legal Guardians of Brain Balance Students

1. What is your child's biological sex?
2. What is your child's age (in years)?
3. What grade is your child in?
4. What is your child's ethnicity?
5. What is your family income?
6. How many languages does your child speak?
7. What language(s) do you primarily speak at home?
8. Highest level of Mother's education
9. Highest level of Father's education
10. How many hours of sleep does your child normally get per day?
11. What time does your child normally go to bed?
12. Your child sleeps about the same amount each day?
13. Your child struggles to get to sleep at bedtime?
14. How many times does your child normally wake up during the night?
15. Your child has difficulty getting out of bed in the morning?
16. On average, how often does your child participate in physical activity outside of school (e.g., sports, running, jumping rope, etc.) lasting more than 30 minutes per week?
17. Please list any sports your child participates in:
18. How often does your child play video games?
19. How often does your child play with their friends?
20. How often does your child have trouble concentrating?
21. How often does your child have trouble getting motivated?
22. How often does your child have trouble completing tasks?
23. How often does your child need redirection to complete a task?
24. How often does your child worry about things?
25. How often does your child feel sad?
26. How often do your child's worries keep them from engaging in activities they enjoy?
27. Does your child have a medical diagnosis?
28. Please list any of your child's diagnoses:
29. Please list any medication your child is currently prescribed:

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