The consistency and cognitive predictors of children's oral language, reading, and math learning profiles

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ABSTRACT

Efforts to understand learning disorders in children by focusing on specific domains and within restricted ability ranges have failed to identify consistent and stable learning profiles. Given evidence for dimensional distribution of oral language, reading, and mathematical skills among those identified with and without learning disorders, examining learning across a range of abilities and domains should provide a better estimate of learning profiles. The present study examined the 1-year stability of cross-domain learning profiles and associated cognitive characteristics of 327 children. Results revealed highly stable profiles with 95% of participants remaining in the same learning profiles across data years. Generally similar performance across domains was observed for three profiles (below average, average, above average) comprising 63% of the sample, with relatively specific differences in oral language or reading characterizing the remaining profiles. Cognitive measures and teacher ratings accurately predicted learning profile in about 55% of participants either at the time of testing or in the following year. The most effective models for categorizing learning profiles all included teacher ratings of reading. Cognitive measures of verbal working memory, verbal intelligence, phonological awareness, symbolic comparison, and visuospatial working memory were also important contributors to classification. The findings indicate that examining learning across domains, abilities, and time has the potential to inform our conceptualization of learning disorders and associated cognitive strengths and weaknesses.

1. Introduction

In the area of learning disabilities, there has long been interest in identifying and understanding common impairment profiles for which specific interventions might be designed. Nevertheless, efforts to identify stable profiles of common impairment have met with limited success (e.g., Conti-Ramsden & Botting, 1999; Mazzocco & Myers, 2003; Peterson, Pennington, Olson, & Wadsworth, 2015). Several methodological reasons could account for the lack of consistent findings including the focus on children in the low range of performance on measures of interest (e.g., Hendriksen et al., 2007), the focus on one sphere of learning (e.g., Morris et al., 1998), and the reliance on cross-sectional study (e.g., Bartelet, Ansari, Vaessen, & Blomert, 2014; Sprenger-Charolles, Cole, Lacert, & Serniclaes, 2000; Tomblin & Zhang, 1999). Similar confusion emerges from studies aimed at understanding the cognitive underpinnings of learning disabilities, which could be related to the investigation of children with varying profiles and the inclusion of a limited number of cognitive measures. An assumption

motivating the current study is that progress in both of these areas could be improved if a broad range of cognitive predictors were examined for stable learning profiles. In our previous work, Archibald, Oram Cardy, Joanisse, and Ansari (2013) took an epidemiological approach to examining language, reading, and math profiles in over 1000 unselected 6-to-9-year-old children, and identified 6 learning profiles. The purpose of the present study was to examine the stability of these learning profiles and their cognitive underpinnings in a subset of the original sample for whom we had 1-year follow up data.

It is well recognized that some children experience unexpected difficulties learning their native language or learning to read, write, or do mathematics at school. The considerable interest aimed at understanding the patterns in these individual differences has largely been aimed at the individual domains of language, reading, or mathematics. Children with an unexpected delay in the onset or development of language have been described as having a developmental language disorder (DLD; also known as specific language impairment; Bishop, Snowling, Thompson, Greenhalgh, & the CATALISE-2 consortium,

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2017), and those with an unexpected difficulty in learning to read or do math have been considered to have dyslexia or dyscalculia, respectively. With a view to understanding profiles and determining possible interventions, considerable research has focused on discovering the unique cognitive mechanisms associated with each of these disorders (language: Conti-Ramsden & Botting, 1999; Conti-Ramsden, Crutchley, & Botting, 1997; reading: Boder, 1973; Stanovich, 1980; Liberman & Shankweiler, 1985; math: Bartelet et al., 2014; von Aster, 2000).

Two lines of evidence suggest that a focus on specific domains and disorders to understand learning patterns is problematic. First, within each of the domains, children with DLD, dyslexia, and dyscalculia have been considered to be a heterogeneous group (Bishop, 2006; Soriano-Ferrer & Piedra Martinez, 2017; Träff, Olsson, Östergren, & Skagerlund, 2015). This heterogeneity has not been explained by the identification of stable and reliable subtypes within groups (language: Conti-Ramsden & Botting, 1999; Tomblin, Zhang, Buckwater, & O'Brien, 2003; reading: Peterson et al., 2015; math: Mazzocco & Myers, 2003). As well, this single domain approach fails to recognize the high comorbidity observed across conditions (see Archibald et al., 2013). Importantly, these overlaps are observed not only in language, reading, and math performance, but also in the cognitive deficits associated with DLD, dyslexia, and dyscalculia (see Archibald et al., 2013). Taken together, this evidence suggests that examining learning across domains has the potential to inform our understanding of learning profiles and their underlying cognitive associates. Indeed, such work could contribute to the development of new models of learning patterns previously masked by a single-domain approach.

A second problem with the study of individuals with specific disorders is the focus on a narrow range of performance distribution. Learning profiles may be poorly estimated by limiting analyses to those scoring in the low range of ability. Importantly, this attention to those with learning disabilities appears unwarranted in light of evidence suggesting no clear distinction between those with and without disorder (language: Dollaghan, 2004, 2011; reading: Kuppen & Goswami, 2016; math: Piazza et al., 2010; Landerl, 2013). This continuity in developmental trajectories provides strong rationale for investigating learning patterns across the full range of performance (see also, Elliott & Grigorenko, 2014). A comprehensive, data-driven model reflecting learning across domains and performance range has the potential to provide insight into questions related to learning profiles and their stability, and clarity regarding the cognitive mechanisms underlying learning patterns.

We took just such a data-driven approach in our previous study examining patterns of performance across the domains of language, reading, and math without a priori constraints on possible profiles (Archibald et al., 2013). We recruited an unselected, epidemiological sample of 1120 children aged 6;0 to 9;11 years to assess whether learning profiles fell into distinct subtypes. Based on a cluster analysis of performance on measures of language, reading, and math, six unique clusters were identified. The first two profiles reflected good or poor performance across all measures; three showed specific learning profiles involving either relatively weak language, weak reading, or weak math; and the sixth showed weaknesses in both math and reading. In the present study, we re-examine these profiles and their stability over a 1-year period in a subset of the original group for whom we had follow up data.

We also planned to examine the potential links between observed subtypes and specific cognitive processes. Identifying cognitive processes underlying learning disabilities is of considerable interest due to the promise such findings might hold for both early identification and appropriate intervention. Although a number of candidate cognitive processes have been studied in relation to language, reading, and math impairments, the area lacks a comprehensive, cross-domain approach resulting in a confusing array of findings suggestive of both specific and nonspecific links. Take, for example, the area of phonological processing: Although phonological awareness deficits have been specifically linked to dyslexia (Kuppen & Goswami, 2016), phonological processing has also been associated with arithmetic fact retrieval in math (De Smedt & Boets, 2010; De Smedt, Taylor, Archibald, & Ansari, 2010), and deficits have been considered characteristic of DLD (Bishop & Snowling, 2004). Similarly, specific deficits in rapid naming and magnitude comparison have been implicated in dyslexia and dyscalculia, respectively, but children with DLD have also been found to have impairments in rapid naming (Coady, 2013) and digit magnitude comparison (Donlan, Cowan, Newton, & Lloyd, 2007). As well, all groups have been found to have working memory impairments (DLD: Archibald & Gathercole, 2006; dyslexia: Gottardo, Stanovich, & Siegel, 1996; dyscalculia: Swanson & Sachse-Lee, 2001), although more specific links have been suggested with language when the to-be-recalled stimuli are verbal (Archibald & Gathercole, 2007), and with math when the stimuli are visuospatial in nature (Menon, 2016). It may be, too, that cognitive reasoning as measured by verbal and nonverbal intelligence could show differential linkages with learning patterns.

Clearly, examining associations between cognitive processes and learning profiles identified empirically across the domains of language, reading, and math has potential for clarifying these relationships. It could be particularly informative to explore the stability of associations between learning abilities and potential cognitive mechanisms over time. Cognitive predictors have been examined for individual learning disorders (e.g., DLD: van Daal, Verhoeven, & van Balkom, 2009; dyslexia: Carroll, Solity, & Shapiro, 2016), but no studies have investigated such predictors across learning domains and longitudinally. The present study was particularly well placed to provide an initial exploration of associations between cognitive processes and stable learning profiles over a 1-year period.

It should be noted that measures of cognitive processes have been found to explain only a modest ($< 50\%$) amount of variance in children's learning profiles for language (van Daal et al., 2009), reading (Ruffing, Sophie Wach, Spinath, Brünken, & Karbach, 2015), and math (Seethaler, Fuchs, Star, & Bryant, 2011). Interestingly, more global teacher ratings of academic and cognitive skills have consistently been found to be related to outcomes in language (Bedore, Peña, Joyner, & Macken, 2011; Gilmore & Vance, 2007), reading (Gallant, 2013; Titley, D'Amato, & Koehler-Hak, 2014), and math (Gallant, 2013; Teisl, Mazzocco, & Myers, 2001). Therefore, we also examined the extent to which teacher ratings provide additive value beyond direct measures of cognitive processes in explaining learning profiles. Teacher ratings of children's language, reading, and math learning were acquired, as well as judgments of memory, attention, and social interaction. The extent to which these ratings uniquely contributed to the discrimination of identified learning profiles beyond what is predicted by measures of relevant cognitive processes was evaluated.

In the present study, elementary school children completed measures of learning in the areas of language, reading, and math, as well as cognitive measures of phonological awareness, rapid naming, magnitude comparison, verbal and visuospatial working memory, and verbal and nonverbal intelligence. Assessments were acquired at an initial time point and at 1-year follow up. As well, teachers made independent ratings of children's language, reading, math, memory, attention, and social interaction. One aim of the study was to examine the patterns of performance in children's measured language, reading, and math learning in comparison to our previous cluster analysis (Archibald et al., 2013) of which the current group was a subset. We were particularly interested in the stability of the identified learning profiles across the 1-year time period spanned by the current study, both in terms of the profiles themselves and the membership of individual children. A second aim was to describe the extent to which our cognitive measures and/or teacher ratings could predict learning profiles both within the respective year of membership, and in the subsequent year. High discrimination of learning profiles based on cognitive abilities would provide support for our data-driven approach. As well, findings that teacher ratings were a unique predictor of learning

profiles would indicate the separable contribution of these measures.

2. Methods

The Nonmedical Research Ethics Board at The University of Western Ontario approved all procedures in this study.

2.1. Participants

The children in this study were participating in a longitudinal study over an 18-month period with data collected during each of two consecutive school years. During the first school year, the present participants were part of a screening sample, an epidemiological cohort of 1120 children who completed a screening protocol consisting of language, reading, and math tasks and described in detail in our initial report of this work (Archibald et al., 2013). In addition to this screening measure, the participants in this study completed (1) a battery of standardized tests during the final two months of the same school year (Year 1) as the screening measure (and within 4.4 months on average; $SD = 1.1$), and (2) the same battery of standardized tests in the subsequent year (Year 2). As described in detail in Archibald et al. (2013) the current sample is a selected sample because participants were selected to complete this additional testing based on screening performance such that those scoring in the average or below average range were about equally represented. A total of 327 children (Mage = 7 years; 10 months; SDage = 1;1; Age range 6;0–9;11; 145 females) completed the Year 1 measures included in the learning profile analysis in the present study. Of these, 276 (Mage = 9 years; 3 months; SDage = 1;1; Age range 7;3–11;5; 124 females) completed testing at Year 2. Levels of maternal education (provided by 308 parents on a 6-point scale) for the Year 1 ($M = 3.97$, $SD = 1.7$) and Year 2 ($M = 4.05$, $SD = 1.7$) participants did not differ. As well, those participants lost to follow up (20 females; 28 males) came from various schools in the sample (with no discernable pattern), and did not differ from the full participant group on age at study entry ($M = 8;0$, $SD = 1.1$) or maternal education ($M = 3.56$, $SD = 1.8$).

2.2. Procedures

Study participants completed 7 individual study sessions (4 in Year 1 and 3 in Year 2) in a quiet room in their school and each involving tasks administered by a trained research assistant (see Table 1). During Year 1, children completed a 10-min screening protocol including math and reading tasks (and a sentence recall task not employed in the current study), and within approximately 4 months, three additional visits occurring one week apart (in May and June of the academic year) and involving standardized tests of language, reading, math, and cognitive processes (verbal and visuospatial short-term and working memory, phonological awareness, nonverbal intelligence, verbal

Table 1
Measures completed during each academic year of the study.

	Year 1	Year 2
February	May/June	May/June
Word reading	Oral language	Oral language
Nonword reading	Reading fluency	Reading fluency
Math fluency	Math fluency	Math fluency
	Calculations	Calculations
	Verbal & visuospatial short-term & working memory	Verbal & visuospatial short-term & working memory
	Nonverbal & verbal intelligence	Nonverbal & verbal intelligence
	Phonological awareness	Phonological awareness
	Rapid naming	Magnitude comparison

intelligence, and rapid naming). In Year 2, all study measures were completed during three additional visits occurring one week apart in May and June of the academic year with the exception of the rapid naming tasks, and the addition of magnitude comparison tasks. In addition, some teachers (Year 1: $n = 296$; Year 2: $n = 267$) completed rating scales of children's learning and cognitive skills.

2.3. Language and academic measures

To examine learning profiles across the domains of language, reading, and mathematics, the following measures were completed in each domain. Published scaled or standard scores were used for all tests except as indicated.

2.3.1. Oral language
Three subtests were completed from the *Clinical Evaluation of Language Fundamentals, 4th edition* (CELF-IV; Semel, Wiig, & Secord, 2003). In the *Concepts and Following Directions* subtest, the child pointed to aspects of a picture following a spoken instruction. For *Recalling Sentences*, the child repeated sentences immediately after hearing them and for *Formulated Sentences*, created a sentence using a given word.

2.3.2. Reading
The *Test of Word Reading Efficiency* (Torgensen, Wagner, & Rashotte, 1999) was administered and involves the number of words or nonwords read, respectively, in 45 s on the *Sight Word Efficiency* (SWE) subtest and the *Phonemic Decoding Efficiency* (PDE) subtest. The *Reading Fluency* subtest of the *Woodcock Johnson Test of Achievement III* (WJ III; Woodcock, Mather, & McGrew, 2006) was also administered and involves reading a sentence and answering yes/no questions.

2.3.3. Math
The *Math Fluency* and *Calculations* subtests of the WJ III were completed. Math Fluency involves the rapid application of basic addition, subtraction, and multiplication questions as quickly and accurately as possible for three minutes. In the Calculations subtest, the child was asked to complete mathematical operations.

2.4. Cognitive measures

In order to examine the relationship between cognitive mechanisms and learning profiles, a broad range of cognitive measures were completed as follows.

2.4.1. Working memory
Eight subtests from the *Automated Working Memory Assessment* (AWMA; Alloway, 2007) were administered. Measures tapping phonological short-term memory involved immediate repetition of numbers or nonword forms (*Digit Recall, Nonword Recall*), and those tapping visuospatial short-term memory required recall of locations (*Dot Matrix, Block Design*). Verbal working memory measures involved recall of counts or final words after counting or processing a sentence, respectively (*Counting Recall, Listening Recall*), while those involving visuospatial working memory required the recall of location or orientation after identifying a different shape or mentally rotating an image, respectively (*Odd One Out, Spatial Recall*). Based on published subtest standard scores, composite scores were created for verbal working memory (Digit Recall; Nonword Recall; Counting Recall; Listening Recall) and visuospatial working memory (Dot Matrix; Block Design; Odd One Out; Spatial Recall) by averaging corresponding standard scores. It should be noted that the averaging of same-domain short-term and working memory scores in this way is supported by studies examining factor structure of such tasks (Archibald, 2013; Shah & Miyake, 1996).

2.4.2. Intelligence
The four subtests of the *Wechsler Abbreviated Scale of Intelligence*

(WASI; Wechsler, 1999) were administered. The nonverbal intelligence subtests included *Block Design*, in which the child arranged blocks to match a model, and *Matrix Reasoning*, which involved choosing a picture to complete a pattern. The verbal intelligence subtests included *Vocabulary*, in which the child provided definitions, and *Similarities*, which involved identifying related pictures or describing similarities between words.

2.4.3. Phonological awareness

Each child was asked to isolate and delete a phoneme from a word in the *Elision* subtest of the *Comprehensive Test of Phonological Processing* (CTOPP; Wagner, Torgensen, & Rashotte, 1999). For example, say 'stop', say it again without saying 't'.

2.4.4. Rapid naming

Each child completed a *rapid object naming task* (dog, hand, book, chair) involving naming rows of pictures presented on a paper card with a 5-row X 10-column grid of the elements. Participants were instructed to accurately name aloud each picture across rows as quickly as possible beginning in the upper left picture and ending at the lower right picture. The time required (in seconds) to name all the items in the grid was recorded. In order to create age-adjusted scores for this task, z-scores were calculated based on age year bands for the sample at Year 1 (6;0–6;11: $n = 45$; 7;0–7;11: $n = 100$; 8;0–8;11: $n = 97$; 9;0–10;4: $n = 85$).

2.4.5. Magnitude comparison

Each child completed a symbolic (56 digit pairs) magnitude comparison task involving the crossing out of the larger of two digits working as quickly and accurately as possible for one minute (see Nosworthy, Bugden, Archibald, Evans, & Ansari, 2013). In order to create age-adjusted scores for this task, z-scores were calculated based on age year bands for the sample at Year 2 (7;0–7;11: $n = 36$; 8;0–8;11: $n = 90$; 0;0–9;11: $n = 78$; 10;0–11;4: $n = 75$).

2.4.6. Teacher ratings

Each participant's classroom teacher was asked to use a 3-point scale (1 = not concerned; 2 = somewhat concerned; 3 = definitely concerned) to rate the child's cognitive skills and learning. Specifically, the teacher was asked 'How concerned are you about this child's…', and the descriptors included 'attention', 'reading', 'math abilities', 'ability to express him/herself orally', 'social interaction', and 'memory skills'.

2.5. Data analysis

For all of the standardized tests/subtests included in the battery (tests of language, reading, math, working memory, phonological awareness, intelligence), published internal consistencies (test-retest reliability, alternate form reliability, Rasch analysis) ranged from 0.71 to 0.90. Reliability for the rapid naming and number comparison tasks have been reported in our related work to be 0.73 and 0.72, respectively (Archibald et al., 2013). These acceptable reliabilities were considered adequate for inclusion in the modeling analyses completed.

In order to explore patterns of unique learning profiles, we included our language and academic measures (8 measures) in a Latent Profile Analysis (LPA), a Gaussian mixture modeling approach used to identify latent categories from multivariate continuous data (completed in Mplus 7.4; Muthén & Muthén, 1998–2017). Although similar to clustering techniques as used in our previous study (Archibald et al., 2013), the mixture modeling framework of LPA better accounts for the probabilistic nature of group membership and provides a better estimate of transitions across time. It should also be noted that the maximum likelihood estimator employed in the Mplus LPA approach handles nonnormality of data, and data transformations are not recommended (Muthén & Muthén, 1998–2017).

LPA models were estimated for 2–9 classes for the Year 1 and Year 2

data separately. Model fit was evaluated based on the Bayesian information criterion (BIC), with lower BIC indicating better fit; a bootstrap likelihood ratio test (BLRT) examines whether there is significant improvement in model fit when estimating k classes relative to the $k - 1$ class. Recent simulation work suggests that the BLRT is the most sensitive index for identifying the correct number of classes in models similar in number of indicators and sample sizes to those estimated here (Nylund, Asparouhov, & Muthén, 2007). When statistical information yielded equivocal information for model selection, we inspected class sizes and whether solutions were consistent across data years. We planned to compare the results of the LPA to our earlier report (Archibald et al., 2013) of learning profiles based on our screening measures from our larger cohort ($n = 1120$). Notably, data from 5 measures in the current Year 1 sample of 327 participants overlapped with that of the earlier cohort (Sight Word Reading; Phonemic Decoding Efficiency; Math Fluency; Reading Fluency; Calculations), however the 2013 report employed a different sentence recall task (Redmond, 2005) as an estimate of language, and did not include the Reading Fluency or Calculations subtests.

We then examined the extent to which our cognitive and rating measures could predict the learning profile to which a participant was assigned using stepwise discriminant function analysis both within and across the Year 1 and Year 2 data using SPSS 24 (IBM Corp, 2016). Prior probabilities were based on group size in all cases. We first planned to complete analyses with the cognitive measures and teacher ratings/maternal education separately, and then with significant predictors in the same model.

3. Results

Overall sample means for the language, reading, and math measures are shown in Table 2. The means ranged from 87 to 103, which is in keeping with the composition of the sample as described in the methods section (i.e., oversampling of participants scoring in the low range on the original screening measure). The overall mean was within 4 standard score points of 100 for all measures except Concepts and Following Directions, Math Fluency, and Calculations. Given these differences, we planned to analyze patterns in the results relative to the overall sample mean for each measure. Skew was less than |1| for all measures, and kurtosis was less than |1.2| for all measures except Calculations at year 1 and 2.

Comparing the current sample to the screening sample reported in Archibald et al. (2013), the two samples did not differ in terms of age or sex distribution, although the current sample scored, on average, about 5 standard score points lower on the overlapping measures: Sight word efficiency, 99.3 ± 12.7 and 105.1 ± 14.0, Phonemic decoding efficiency, 99.1 ± 11.3 and 105.1 ± 13.5, Math Fluency, 87.4 ± 13.9 and 92.7 ± 14.7 and a sentence recall measure not reported here, 94.9 ± 17.1 and 100.1 ± 15.0, respectively, for means plus/minus standard deviations of the current and screening samples ($t > 7.0$, $p < .001$, all cases). As well, there was a small but significant difference ($t > 3$, $p < .005$) in maternal education levels (current sample: $M = 3.97$, $SD = 1.7$; screening sample: $M = 4.34$, $SD = 1.6$). These data indicate that the study findings may not generalize to children who achieve very high standardized scores on language, reading, or math measures. It should also be noted that those who did ($n = 276$) or did not ($n = 48$) contribute data at Year 2 did not differ on any of the language, reading, or math measures ($t < 1.6$, $p > .05$, all cases).

3.1. Latent profile analysis of language, reading, and math learning profiles

In exploring the unique learning profiles represented in our data, the LPA completed on the language (Concepts and Following Directions; Recalling Sentences; Formulated Sentences), reading (Sight Word Reading; Phonemic Decoding Efficiency; Reading Fluency), and math measures (Math Fluency; Calculations) revealed similar model fit

Table 2
Demographics and mean scores (standard errors) for language and academic measures in each of the profiles and overall.

Measure	Profile						
	1	2	3	4	5	6	Overall
Year 1							
n (number of females)	14 (4)	39 (10)	75 (30)	33 (13)	122 (62)	44 (26)	327 (145)
Age (years)	8.6 (0.7)	8.5 (1.0)	7.8 (1.0)	8.1 (1.2)	7.7 (1.0)	7.5 (1.2)	7.9 (1.1)
Language							
Following directions	79^{ab} (3.5)	72^a (1.8)	**94^b (1.4)**	78^a (1.9)	102^c (0.9)	108^c (1.4)	94.0 (0.9)
Recalling sentences	83^a (3.0)	83^{ab} (1.9)	93^c (1.3)	**89^{bc} (2.1)**	103^d (1.1)	106^d (1.8)	96.5 (0.8)
Formulating sentences	80^a (2.8)	90^a (2.0)	**100^b (1.4)**	98^b (1.6)	109^c (1.0)	114^c (1.2)	102.9 (0.8)
Reading							
Sight word efficiency	60^a (1.5)	87^b (1.4)	92^b (0.8)	**105^{cd} (1.3)**	105^e (0.6)	112de (1.0)	99.3 (0.7)
Phonemic decoding	73^a (1.1)	89^b (1.2)	93^b (0.9)	**104^c (1.4)**	103^c (0.6)	112^d (1.0)	99.1 (0.6)
Reading fluency	66^a (2.7)	84^b (0.9)	93^c (0.8)	**102^d (1.2)**	104^d (0.6)	116^e (1.1)	98.7 (0.7)
Math							
Math fluency	70^a (2.5)	74^a (1.4)	**85^b (1.3)**	79^{ab} (1.6)	94^c (1.0)	97^c (2.2)	87.4 (0.8)
Calculations	60^a (4.8)	74^{ab} (2.3)	**94^c (1.3)**	80^b (3.1)	100^{cd} (1.0)	107^d (2.0)	92.3 (1.0)
Year 2							
n (number of females)	10 (4)	36 (8)	63 (24)	29 (14)	95 (48)	43 (26)	276 (124)
Age (months)	10.2 (0.7)	9.9 (1.0)	9.3 (1.1)	9.4 (1.1)	9.0 (1.0)	8.9 (1.2)	9.26 (1.1)
Language							
Following directions	**81^{ab} (4.6)**	74^a (1.9)	**94^b (1.6)**	86^b (2.4)	103^c (1.0)	106^c (1.6)	94.8 (0.9)
Recalling sentences	**86^a (4.3)**	85^a (2.0)	93^a (1.6)	90^a (2.1)	106^b (1.1)	109^b (1.9)	98.4 (0.9)
Formulating sentences	78^a (4.1)	83^a (2.3)	**95^b (1.7)**	91^{ab} (2.7)	105^c (1.1)	110^c (1.7)	98.1 (0.9)
Reading							
Sight word efficiency	67^a (1.7)	85^b (1.1)	92^c (0.9)	113^d (1.1)	105^e (0.8)	118^d (1.2)	100.9 (0.9)
Phonemic decoding	70^a (1.7)	86^b (1.4)	91^b (1.0)	111^c (1.8)	**101^d (0.8)**	116^c (1.4)	99.1 (0.9)
Reading fluency	66^a (2.5)	85^b (1.2)	93^c (0.7)	**101^d (1.1)**	103^d (0.7)	115^e (1.4)	98.5 (0.8)
Math							
Math fluency	69^a (2.6)	72^a (1.4)	**86^b (1.2)**	80^{ab} (1.6)	93^c (1.0)	103^c (1.6)	87.9 (0.8)
Calculations	55^a (6.2)	69^{ab} (2.6)	**88^c (1.5)**	74^b (2.7)	94^{cd} (1.0)	101^d (1.6)	86.7 (1.0)

Note: (1) All non-bolded means are significantly different from the overall sample mean for respective measure, $p \leq .001$ (all remaining cases, $p \geq .004$). (2) Means with matching superscripts in the same row are not significantly different, $p < .001$ (all remaining cases, $p \geq .006$). (3) Profile scores between Year 1 and 2 did not differ significantly ($p > .001$, all cases) for all measures except (a) Profile 5, calculations ($p < .001$) and (b) Profile 6, sight words efficiency ($p < .001$). (4) Profile 1–6 labels, respectively: well below average, below average, reading efficiency weakness, math weakness, average, above average.

indices across the 6, 7, and 8 class models for the Year 1 data (BIC Range: 20,224.26-20,225.92 compared to 20,242.81 and 20,230.17 for 5 and 9 class solutions, respectively). In the Year 2 data, the 6-class model had the lowest BIC (17,301.64 compared to 17,321.54 and 17,313.18 for 5 and 7 class solutions, respectively). The BLRT indicated that adding additional classes significantly improved model fit. Thus, this index provided little guidance about model selection. Entropy was good in all models (values > 0.80). In order to select the most consistent results across these longitudinal time points, and with our previous report of a 6-cluster solution to describe our screening sample (Archibald et al., 2013), we considered the 6-class solution to be the most appropriate model for both our Year 1 and Year 2 LPAs.

Table 2 shows estimates of the class means and standard errors for all language and academic measures included in the LPA, as well as class demographics related to size, sex, and age for each class and data year. Given the differences in the overall sample standardized score means across measures (as outlined above), relative strengths and weakness in these learning profiles across measures must be interpreted relative to the overall sample mean for each measure (refer to bolding in Table 2 for means that do or do not differ from the overall sample mean). In order to facilitate this process, Fig. 1 presents difference scores for each measure calculated by subtracting the class mean from the overall sample mean for the Year 1 and Year 2 data, together with a corresponding figure based on our YEAR data. Probably the most striking pattern across these profiles is a gradation based on severity with profiles 1 and 2 reflecting well below and below average scores, respectively, and profiles 5 and 6 reflecting above and well above average scores, respectively. The two other average profiles show a relative weakness in reading efficiency (profile 3) or math (profile 4).

3.1.1. Transitions across years

Next, we completed a latent transition analysis, which determines the probability of profile membership at Year 2 given profile membership at Year 1. In the transition model, there is separate modeling of the time points, but information from both time points is used to inform class membership. As a result, all 327 participants are assigned to a profile at each time point. Table 3 shows the probability values, and the actual class sizes for profile transitions from Year 1 to Year 2. Probabilities of remaining in the same class were > 0.86, in all cases. > 95% of all participants were classified into the same profile across years. Of the 15 movers, 7 were in profile 5 (average), 2 in each of profiles 1 (well below average) and 4 (relative math weakness), and 3 in profile 3 (relative reading efficiency weakness) at Year 1. As well, movers were older ($M = 8.5$ years, $SD = 1.0$) than those who stayed in the same profile ($M = 7.9$ years, $SD = 1.1$) on average ($U = 1499.5, p = .019$).

3.2. Predictors of learning profiles

3.2.1. Cognitive predictors of learning profiles

For all of the cognitive measures (phonological awareness, nonverbal intelligence, verbal intelligence, verbal working memory, visuospatial working memory, rapid object naming, symbolic comparison), sample means were close to the standardized mean (99–103) and the standard deviation ranged from 10 to 15 (exception: For rapid object naming and symbolic comparison, the means were 0 and SDs, 1). In the majority of cases, skew was < 1 (exception: rapid object naming), and kurtosis was < 3 (exceptions: visuospatial working memory, nonverbal working memory, symbolic comparison, rapid object naming). We completed 3 stepwise discriminant function analyses predicting LPA class based on these cognitive measures for data within each year (Within Year 1; Within Year 2), and for the Year 1 cognitive measures
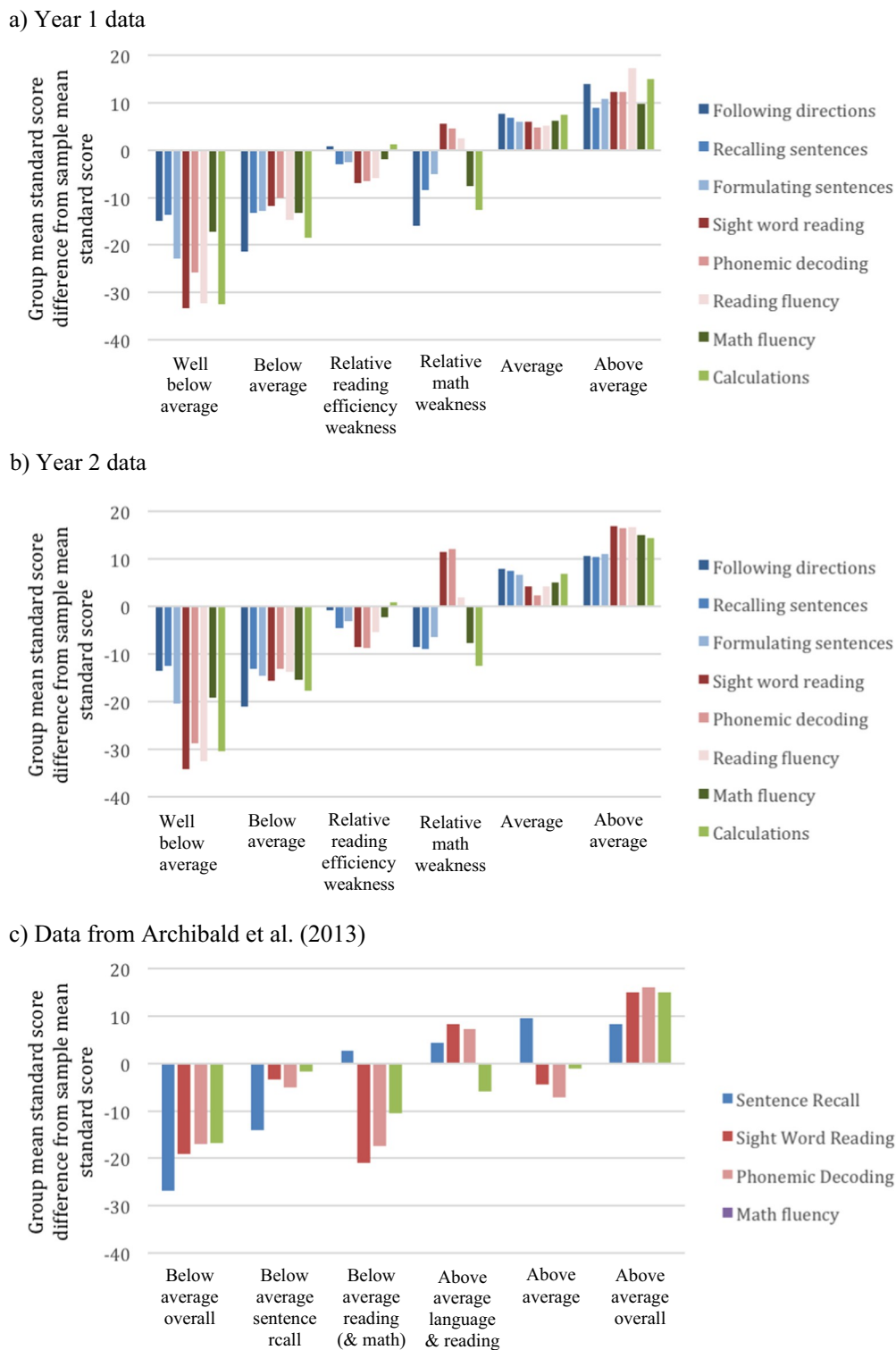
a) Year 1 data

b) Year 2 data

c) Data from Archibald et al. (2013)

Fig. 1. Difference scores between class mean and full sample mean for each measure and profile for a) Year 1 data, b) Year 2 data, and c) data from Archibald et al. (2013).

predicting Year 2 learning profiles (Year 1-to-2). In each case, the model showed a significant association between class membership and some of the cognitive measures $F > 12.5$, $p < .001$, all cases. Table 4 summarizes the percent variance explained, percent cases correctly classified, and significant functions for each exploratory model. The models explained 59–65% of the data, but correctly classified only about 50% of cases. Measures with moderate to high loadings on significant functions included phonological awareness, verbal working

memory, and verbal intelligence. Eigenvalues were large (> 1) for the first function in each model only. In the Within Year 1 model, phonological awareness group centroids were markedly low for profiles 1 (well below average) and 2 (below average) and high for profile 6 (well above average), and verbal working memory group centroids were markedly low for profile 2 (below average). In the Within Year 2 model, verbal intelligence group centroids were markedly low for profile 2 (below average), and group centroids for verbal working memory were

Table 3
Probability (p) of Year 2 profile given Year 1 profile, and corresponding actual class sizes (n).

Year 2 Profile →	1		2		3		4		5		6		Total *n* (Year 1)
Year 1 Profile ↓	*p*	*n*	*p*	*n*	*p*	*n*	*p*	*n*	*p*	*n*	*p*	*n*	
1. Well below average	0.86	12	0.13	2	–	0	–	0	–	0	–	0	14
2. Below average	–	0	1.00	39	–	0	–	0	–	0	–	0	39
3. Relative reading efficiency weakness	–	0	0.03	1	0.89	72	–	0	0.08	2	–	0	75
4. Relative math weakness	–	0	–	0	0.10	2	0.90	31	–	0	–	0	33
5. Average	–	0	–	0	0.03	1	0.05	4	0.89	114	0.04	3	122
6. Above average	–	0	–	0	–	0	–	0	0.01	0	0.99	44	44
Total *n* (Year 2)		12		42		75		35		116		47	

Note: A double-dash (–) indicates a highly unlikely Year 1-Year 2 profile combination (*p* < .005).

Table 4
Discriminant function models for Year 1 and 2 cognitive measures predicting respective learning profile (within year), and for Year 1 cognitive measures predicting 2 learning profile.

	Within Year 1		Within Year 2		Year 1 predicting Year 2	
Data year for cognitive predictors	Year 1		Year 2		Year 1	
Data year for profile membership	Year 1		Year 2		Year 2	
% variance explained	59%		65%		59%	
% cases correctly classified	49.8%		49.5%		48.0%	
# significant functions (eigenvalues)	2 (1.24; 0.07)		2 (1.64; 0.06)		2 (1.24; 0.07)	
Measures relevant to each function[a]	Phonological awareness	Verbal WM	Verbal intelligence	Verbal WM	Phonological awareness	Verbal WM
Function centroids[b] for each profile						
1. Well below average	−1.7	−0.6	−0.8	−1.2	−1.9	−0.6
2. Below average	−1.2	−1.4	−1.3	−1.2	−1.2	−1.4
3. Reading efficiency weakness	−0.4	−0.2	−0.3	−0.3	−0.3	−0.3
4. Math weakness	0.1	−0.3	−0.5	−0.3	0.1	−0.1
5. Average	0.3	0.4	0.5	0.5	0.3	0.4
6. Above average	1.1	0.7	0.8	0.8	1.0	0.7

[a] Relevant measures were considered those with factors loadings > 0.4 (moderate-to-high) on significant functions; WM = working memory.
[b] Function centroids are based on discriminant functions scores ($M = 0$, $SD = 1.0$).

markedly low for profiles 1 (well below average) and 2 (below average). The pattern for the Year 1-to-2 model was almost identical to that of the Within Year 1 model.

3.2.2. Contribution of teacher ratings or maternal education

For teacher ratings (out of 3) of attention, reading, math, expression, social interaction, and memory skills, ratings of 1 (not concerned) were the most common response. Ratings were similar across areas with means ranging from 1.48 to 1.83 (standard deviations, 0.7–0.8). Skew was < 1.1 and kurtosis was < 3 in all cases. Maternal education varied little in this sample with more than two thirds of responders reporting post-high school education ($M = 3.97$, $SD = 1.7$, skew = −0.3, kurtosis = 1.9). In order to explore whether teacher ratings or maternal education added unique discriminant value, we first completed two preliminary discriminant function analyses in order to limit the number of predictors entered in subsequent analyses. For each year, only the six teacher ratings for the respective year and maternal education were entered as predictors. For the Year 1 data, only teacher ratings of reading and math were retained in the model, and for the Year 2 data, only teacher ratings of reading and memory were retained. In subsequent analyses, only the respective significant teacher rating predictors were included in the relevant Year 1 or 2 models. Given that maternal education was not retained in these preliminary models, maternal education was not included in subsequent analyses.

The final set of three discriminant function analyses predicting the LPA profiles included the cognitive measures as before (phonological awareness, nonverbal intelligence, verbal intelligence, verbal working memory, visuospatial working memory, rapid object naming, and symbolic comparison) but also included the relevant teacher ratings for each year (Year 1: reading, math; Year 2: reading, memory; see above).

All models were significant, $F > 12.5$, $p < .001$ (all cases), and are summarized in Table 5. The percent of variance explained was somewhat higher compared to the models with the cognitive predictors only (72–75% vs. 59–65%), although the percent of cases classified correctly was only minimally improved (54–56% vs 50%). Teacher ratings of reading loaded on the first function in all three models (i.e., eigenvalues > 1.8, all cases), and group centroids for this function were markedly low in all models for profiles 1 (well below average) and 2 (below average), and relatively high for profiles 5 (average) and 6 (above average). Nevertheless, phonological awareness had high factor loadings on significant functions in two of the models, and verbal working memory (with or without verbal intelligence), in all three models. These models also revealed associations with math-related measures including symbolic comparison for the Within Year 1 model, visuospatial working memory for the Year 2 model, and teacher ratings of math for the Year 1 cognitive/rating measures predicting Year 2 profile membership model. Notably, group centroids were low for profile 4 (math weakness) on the function including symbolic comparison (function 2) in the Within Year 1 model. For the Within Year 2 and Year 1-to-2 models, the visuospatial and teacher ratings of math group centroids were markedly low and relatively low for profile 1 (well below average), respectively. Interestingly, group centroids for the two models including phonological awareness in significant functions did not vary widely (Year 1: −0.3 to 0.4; Year 2: −0.8 to 0.5), with the most notable difference being for profile 4 (math weakness) in the Year 1-to-2 model.

To further investigate the classification accuracy of these models, classification statistics for each profile were examined. For all models, classification accuracy varied considerably across profiles with profiles 2 (below average) and 5 (average) being most consistently classified:

Table 5

Discriminant function models for Year 1 and 2 cognitive measures and teacher ratings predicting respective learning profile (within year), and for Year 1 cognitive measures and teacher ratings predicting 2 learning profile.

	Within Year 1			Within Year 2			Year 1 predicting Year 2			
Data year for cognitive predictors	Year 1			Year 2			Year 1			
Data year for profile membership	Year 1			Year 2			Year 2			
% cases correctly classified	75%			74%			72%			
# significant functions	56.2%			56.2%			53.9%			
Measures relevant to each function[a]	3 (2.1; 0.2; 0.1)			3 (2.2; 0.1; 0.1)			4 (1.9; 0.1; 0.1; 0.1)			
Function centroids for each profile[b]	Teacher rating reading	Verbal WM, verbal IQ, symbolic comparison	Phonological awareness	Teacher rating reading	Verbal WM	Visuospatial WM	Teacher rating reading	Phonological awareness	Verbal WM	Teacher rating math
1. Well below average	−2.9	0.3	0.2	−2.7	−1.0	1.3	−2.8	0.5	−0.2	0.8
2. Below average	−2.6	−0.3	−0.3	−2.8	−0.2	0.02	−2.4	−0.3	−0.1	−0.4
3. Reading efficiency weakness	−0.9	0.3	0.2	−0.8	0.6	−0.2	−0.9	0.3	0.2	−0.01
4. Math weakness	−0.004	−1.0	0.2	−0.5	−0.7	−0.3	0.2	−0.8	0.2	0.3
5. Average	0.9	0.1	−0.3	1.0	−0.1	−0.1	0.9	0.02	−0.3	0.02
6. Above average	1.8	−0.01	0.3	1.7	0.03	0.3	1.7	0.2	0.3	−0.1

[a] Relevant measures were considered those with factors loadings greater than 0.4 (moderate-to-high) on significant functions; WM = working memory.

[b] Function centroids are based on discriminant functions scores (M = 0, SD = 1.0).

Profile 1 (well below average), 10–25%; Profile 2 (below average), 62–74%; Profile 3 (reading efficiency weakness), 48–59%; Profile 4 (math weakness), 26–35%; Profile 5 (average), 77–82%; Profile 6 (above average), 30–42%. Notable classification errors included the classification of Profile 1 as Profile 2 or 3, Profile 2 as Profile 3, and Profile 6 as Profile 5. Classification errors for Profiles 3, 4, and 5 tended to be more broadly distributed.

4. Discussion

In a subset of 327 children from our original large epidemiological sample of 6- to 9-year-olds (Archibald et al., 2013), we used a data-driven approach to classify children into one of six learning profiles, based on performance on language, reading, and math measures. The profiles were consistent with our previous report based on a cluster analysis, but in the present study, were based on two data points spanning a 1-year period and including at least two measures estimating the relevant constructs.

The identified learning profiles largely reflected a gradation in severity from well below to well above average. Four profiles (Profiles 1, well below average; 2, below average; 5, average; 6, well above average) had generally similar performance across the domains of language, reading, and math, and constituted 67% of the entire sample (see also, Moll, Kunze, Neuhoff, Bruder, & Schulte-Körne, 2014). Two other average performing profiles were characterized as having a relatively specific weakness in reading efficiency (Profile 3) or math (Profile 4). The profiles were markedly stable with 95% of participants remaining in the same learning profiles across data years. Profile discrimination based on a range of cognitive measures accounted for only 59–65% of variance in the data, and correctly classified about 50% of cases. When teacher ratings that were significant predictors for each data year (Year 1: reading, math; Year 2: reading, memory) were added to the model, discriminant functions explained 72–75% of variance in the data and correctly classified about 55% of cases. For both predictors of profile membership within the year of testing or in the year following, teacher ratings of reading explained the most variance. Phonological awareness, verbal working memory, and verbal intelligence were significant cognitive predictors regardless of whether or not teacher ratings were included in the model, however, the association with some cognitive predictors (symbolic comparison; visuospatial working memory) was only revealed in the models including teaching ratings. Teacher ratings of math at Year 1 was a significant predictor of profile membership at Year 2. None of the remaining measures significantly predicted profile membership (nonverbal intelligence, rapid object naming, maternal education, or teacher ratings of attention, expressive language, and social interaction).

With regards to the first aim of our study, the presented findings identified a set of highly stable and consistent learning profiles related to language, reading, and math over a 1-year period. Although coherent with our previous work, Archibald et al. (2013) included only four measures of the three learning constructs and employed a cluster analysis, which aims for clusters of roughly equal size. The current results included a minimum of two measures per construct and employed a latent profile analysis, which can provide a better estimate of the relative profile size for the six profiles identified. Although all of the profiles were distinguished from each of the other profiles by at least two of the language, reading, or math measures, the most striking pattern evident was a gradation in severity across profiles. It must be acknowledged that these profiles are unlikely to represent discrete groups but rather dimensional differences. This suggestion is strengthened by our Latent Profile Analysis, which did not point to a single solution but rather showed similar indices across models with 6, 7, and 8 classes.

Somewhat surprisingly, there was remarkable consistency with which participants were classified to the six learning profiles over the one year of the current study. Some previous studies have shown reasonable longitudinal concordance for the presence or absence of impairments at least in the areas of language (Tomblin et al., 2003) or reading (Peterson et al., 2015) if not math (Mazzocco & Myers, 2003); however, stability within subtypes has not been found to be better than fair in the few studies providing such data (Conti-Ramsden & Botting, 1999; Peterson et al., 2015; Silver, Pennett, Black, Fair, & Balise, 1999). Our finding for a broad range of abilities across the domains of language, reading, and math is important because it suggests that examining learning across domains (rather than the more common focus on specific disorders) could identify stable profiles of learning strengths and weaknesses across domains.

It is interesting to consider how the observed profiles map onto the characteristics described for developmental language disorder (DLD, also known as specific language impairment), dyslexia, and dyscalculia. There is a clear correspondence between our relatively specific profiles, Profile 3 (relative weakness in reading efficiency) and Profile 4 (relative weakness in math), and dyslexia and dyscalculia, respectively. Although the sample proportions for Profiles 3 (20%) and 4 (10%) are higher than prevalence reports of dyslexia (5–17%; Shaywitz & Shaywitz, 2003) and dyscalculia (3–6%; Shalev, Auerbach, Manor, & Gross-Tsur, 2000), it must be recalled that Profiles 3 and 4 included many children who did not score in the disordered range on relevant measures and would not qualify for a diagnosis of dyslexia or dyscalculia (despite relative weaknesses). Importantly, these profiles emerged much more clearly in the current study compared to our previous study (Archibald et al., 2013), which again suggests that examining learning broadly may be important to understanding learning profiles and learning disorders.

There was no indication of a profile with a relatively specific weakness in language skills. Although our Archibald et al. (2013) identified a cluster with low scores on our sentence recall measure, the corresponding profile in the present study showed a flat performance across measures (profile 2). Nevertheless, the absence of a relatively specific profile of language impairment is not entirely surprising. As has been observed by other researchers and consistent with our own findings, children with specific impairments in oral language only are relatively rare and may be the exception rather than the rule (Reilly et al., 2014). In the case of DLD, it is much more likely that affected children would have academic difficulties commensurate with their language impairments, which would be entirely consistent with our profiles 1 and 2 (well below average and below average across domains).

The observation of relatively specific learning weaknesses at least for reading efficiency (Profile 3) and math (Profile 4), but generally low learning when language is low is important. It could be argued that language learning is fundamentally different from learning to read or do math. Oral language is learned largely implicitly, whereas reading and math are taught explicitly at school. As well, oral language may be considered another cognitive process that supports the learning of both reading (Hitch, Halliday, Schaafstal, & Schraagen, 1988; NICHD Early Child Care Research Network, 2005) and math (Hitch et al., 1988; Mercer & Sams, 2006). In the present study, we considered language, reading, and math as separate domains of learning given our interest in investigating subtypes related to commonly reported disorders in each of these areas (DLD; dyslexia; dyscalculia). This approach, however, did not allow us to investigate directly the extent to which oral language skills support reading and math. Nevertheless, our findings of relatively specific weakness profiles for reading and math but generally (well) below average profiles when language is weak suggests that it may be possible to distinguish learning profiles either related to oral language constraints or not.

In order to address our second goal, we explored the utility of a series of cognitive measures (only) to discriminate among the observed learning profiles in the present study. In keeping with previous reports (language: van Daal et al., 2009; reading: Ruffing et al., 2015; math: Geary, Bailey, & Hoard, 2009), these models explained 59–65% of the variance in language, reading, and math scores but accurately classified

no > 50% of cases. One reason cognitive measures may be weak predictors of performance on learning tests is that current behavioral tasks only indirectly measure cognitive abilities. Take, for example, concerns regarding the reliability and validity of the multiple tasks considered to measure executive functions (Chan, Shum, Toulopoulou, & Chen, 2008). Given that these indirect measures only imperfectly estimate cognitive constructs, it is likely that the role of cognitive processes is underestimated in models assessing predictors of learning. Of course, another explanation is that we failed to, and are indeed unable to, measure all cognitive processes potentially important to learning.

When teacher ratings were included with cognitive measures in the present work, considerably more variance was explained in the model discriminating our six learning profiles (an increase from approximately 60 to 75%), and classification accuracy was modestly increased (from 50 to 55% of cases correctly classified). As with previous findings (e.g., Kim, Lambert, & Burts, 2013), these results suggest that teacher ratings are useful in discriminating children's learning patterns including ratings of both academic (i.e., reading, math) and cognitive (memory) skills. Importantly, teacher ratings provided 'added value' beyond cognitive measures in discriminating the learning profiles. Further research is needed to understand how to best measure teacher ratings and factors contributing to ratings of children's learning.

An important aspect of the longitudinal design of our study was the ability to examine cognitive predictors of learning profiles over time. At Year 1, a mixed factor discriminated learning profiles comprised of verbal working memory, verbal intelligence, and symbolic comparison (and also, visuospatial working memory, to some extent), whereas the corresponding factor in the follow up data was dependent on verbal working memory skills only. The finding of a mixed factor at the early time point only might reflect the importance of multiple cognitive processes in supporting early learning, in particular. As well, the significance of verbal working memory in all of these models suggests that the facility to retain and manipulate verbal stimuli is an ability that discriminates learning profiles.

Year 1 phonological awareness was important in discriminating learning profiles. Of course, phonological awareness in young children has long been recognized as a significant predictor of later reading outcomes (Hogan, Catts, & Little, 2005). The predictive power of phonological awareness, however, has been found to diminish in older learners (Hogan et al., 2005), a finding entirely consistent with the present observation of negligible contributions of phonological awareness to discriminating learning profiles in our follow-up data specifically. Interestingly, phonological awareness and teacher ratings of reading loaded on separate functions in respective analyses. This finding suggests that teachers were sensitive to factors beyond phonological/decoding skills in making judgements about reading. Surprisingly, rapid automatic naming was not retained in the discriminatory functions reported in the present analyses. This result is difficult to reconcile with previous reports demonstrating at least partially independent influences of phonological awareness and rapid automatic naming on reading (Wolf & Bowers, 1999). It must be acknowledged, however, that we measured rapid automatic naming at only one time point in the present study (Year 1) and with only one measure.

Magnitude comparison for symbolic stimuli contributed to the discrimination of learning profiles, at least at the initial testing point, a finding consistent with previous reports of a unique association between symbolic comparison and math skills (Nosworthy et al., 2013). Symbolic comparison and visuospatial working memory showed an interesting relationship in the present study: These processes loaded on the same discriminatory factor at both data time points but only symbolic comparison was a significant component at Year 1 and only visuospatial working memory at Year 2. Interestingly, visuospatial working memory has been found to be associated with math outcomes in addition to symbolic comparison (Mazzocco & Myers, 2003). The present findings suggest that these two measures, symbolic comparison and visuospatial working memory, may share some explanatory power

in discriminating learning profiles with symbolic comparison more sensitive to patterns in younger learners and visuospatial working memory more sensitive to older learners. It may be, too, that the visuospatial working memory measures in the present study captured more variance in our older learners.

It is of interest that none of our discriminatory function analyses included nonverbal intelligence or maternal education as making a significant contribution to the model. The finding for nonverbal intelligence belies years of debate centering on the discrepancy model limiting diagnoses of learning disabilities to those with a gap between potential as measured by intelligence (IQ) and achievement as reflected in reading or math test scores (Restori, Katz, & Lee, 2009). There is now considerable consensus on eliminating this discrepancy model (Bishop et al., 2017), as would follow from the present results. In fact, the *Diagnostic and Statistical Manual of Mental Disorders* (DSM-5; American Psychological Association, 2013) does not include an IQ-achievement discrepancy in the diagnosis of learning disability. The finding that maternal education did not significantly predict learning profile in our study was surprising, but may be related to the reduced variability in our sample (65% reported post high school levels of education).

The current results do demonstrate that multiple cognitive measures related to language (verbal working memory), reading (phonological awareness, teacher rating of reading), and math (symbolic comparison, visuospatial working memory) may be necessary to understand mechanisms influencing learning profiles characteristic of 6–9-year-old children with a range of abilities in oral language, reading, and math. This suggestion is consistent with findings from a study examining neural systems in learning disabilities (Nicolson & Fawcett, 2007). These researchers argued for an approach that moved from a broad to narrow focus in order to allow identification of both affected circuits and affected components within circuits. Secondary symptoms were considered to have important diagnostic significance for meeting the challenge of differentiating and diagnosing specific developmental disorders with overlapping symptoms.

The clinical implications of the current study relate to the importance of considering a child's learning across domains. Considering learning in language, reading, and math may provide a better understanding of a child's learning characteristics than examining any one domain on its own. The findings provide relatively little support for the measurement of cognitive processes to aid in identification of learning profile, with the exception of phonological awareness and especially in the early grades. The relative strength of teacher ratings of reading observed in the present study is interesting. These were quick judgments made on a 3-point scale, and they explained more variance then any of the cognitive measures. It seemed that the teacher ratings were explaining variance in addition to that of the strongest cognitive measures (i.e., phonological awareness; verbal working memory). Perhaps teacher global ratings more accurately bundle all skills important to a learning domain than any single skill measure can achieve. These suggestions are consistent with findings that parent-report and performance-based measures of executive functions assess different constructs (Ten Eycke & Dewey, 2016). Further the findings call for further evaluation of the potential of teacher ratings in identifying children's learning profiles.

5. Conclusions

In a sample of 327 children ages 6 to 9 years representing a range of abilities in oral language, reading, and math followed over a 1-year period, we observed six learning profiles consistent with our previous report on a larger sample including the present subset of participants (Archibald et al., 2013). The profiles largely represented a severity gradation of generally flat learning profiles, however, two relatively specific profiles involving weaknesses in either reading efficiency or math characterized about one third of the sample. Profile membership was remarkably consistent over the one year of this study. Cognitive

measures and teacher ratings were sufficient to accurately classify just over half of the participants either at the time of testing, or in predicting profile in the following year. Teacher ratings of reading were particularly important in discriminating learning profiles. Cognitive measures related to oral language (verbal working memory, verbal intelligence), reading (phonological awareness), and math (symbolic comparison, visuospatial working memory) were also important contributors to discriminating groups. Indicators of developmental differences across the one year studied in the present work include the importance of multiple cognitive measures, phonological awareness and symbolic comparison in the time 1 discriminatory function, and verbal and visuospatial working memory in the time 2 discriminatory function. The present results demonstrate the utility of examining learning patterns across domains, abilities, and time to investigate stable and consistent learning profiles. The findings have important implications for conceptualizing learning profiles across domains and the associated cognitive processes.

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