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Cognitive subtypes of mathematics learning difficulties in primary education

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ABSTRACT

It has been asserted that children with mathematics learning difficulties (MLD) constitute a heterogeneous group. To date, most researchers have investigated differences between predefined MLD subtypes. Specifically MLD children are frequently categorized a priori into groups based on the presence or absence of an additional disorder, such as a reading disorder, to examine cognitive differences between MLD subtypes. In the current study 226 third to six grade children (*M* age = 131 months) with MLD completed a selection of number specific and general cognitive measures. The data driven approach was used to identify the extent to which performance of the MLD children on these measures could be clustered into distinct groups. In particular, after conducting a factor analysis, a 200 times repeated *K*-means clustering approach was used to classify the children's performance. Results revealed six distinguishable clusters of MLD children, specifically (a) a weak mental number line group, (b) weak ANS group, (c) spatial difficulties group, (d) access deficit group, (e) no numerical cognitive deficit group and (f) a garden-variety group. These findings imply that different cognitive subtypes of MLD exist and that these can be derived from data-driven approaches to classification. These findings strengthen the notion that MLD is a heterogeneous disorder, which has implications for the way in which intervention may be tailored for individuals within the different subtypes.

1. Introduction

Today, children are required to make decisions based on simple number and quantity information every day (Dowker, 2005). Yet approximately 6% of the school-aged children do not have sufficient mathematics skills, despite being of normal intelligence (Desoete, Roeyers, & DeClercq, 2004; Gross-Tsur, Manor, & Shalev, 1996). Still, higher prevalence rates have even been reported when using different methods or more lenient criteria (Barbaresi, Katusic, Colligan, Weaver, & Jacobsen, 2005; Mazzocco & Myers, 2003).

The operationalization and cut-off scores used to define mathematics learning difficulties (MLD) have varied substantially (Moeller, Fischer, Cress, & Nuerk, 2012). Note that as Mazzocco, Feigenson, and Halberda (2011) did, we consider MLD and dyscalculia to be synonymous in this article. We prefer to use MLD in the paper, given that we did not

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measure mathematics performance multiple times and therefore cannot speak to the stability of the mathematics deficit. At present, most researchers agree that children with MLD experience severe difficulties in encoding arithmetic facts into long-term memory (e.g., Geary, 1993; Rousselle & Noël, 2007). Specifically, while typically developing children shift from the use of effortful procedures to solve arithmetic problems, such as finger counting or breaking problems down into multiple steps, to the fast retrieval of facts from long-term memory, children with MLD persist in the use of non-retrieval strategies to solve arithmetic problems.

Arithmetic is a complex ability composed of a variety of skills which seem to rely on different cognitive processes (Dowker, 2005). Accordingly it has been proposed that MLD is likely to be a heterogeneous disorder (Geary, 2010; Kaufmann & Nuerk, 2005; Rubinsten & Henik, 2009). A data-driven study by Von Aster (2000) supports this proposition. Specifically, Von Aster assessed the basic number processing and calculation skills of 93 primary school children who performed poorly in mathematics. Employing a clustering approach, Von Aster (2000) differentiated a poor performance cluster and three different dyscalculia clusters. The latter clusters consisted of children who scored more than one standard deviation below the mean test score of the normal population on at least one subtest. Children in the Arabic subtype exhibited deficits on a number transcoding task and a number comparison task. The cognitive profile of the verbal subtype was characterized by severe problems on a counting task and weak subtraction skills. The children in the pervasive subtype displayed impairments on almost all measures.

In most other MLD classification studies (Jordan, Hanich, & Kaplan, 2003; Rourke, 1993; Shalev, Manor, & Gross-Tsur, 1997), researchers have applied a top-down, a priori approach. They examined the cognitive profiles of MLD subtypes which were specified beforehand based on a priori assumptions derived from prior studies and theories. Consequently they limit the number of subtypes in advance, which could have led on the one hand to a failure to identify all subtypes and on the other hand to the aggregation of two MLD categories with distinct underlying features into one predefined subtype. Moreover, only few studies focused on number-specific cognitive processes (e.g., counting), despite that empirical research has underlined the importance of including these processes in MLD studies (Price & Ansari, 2012). Therefore the current study implemented a data-driven approach, administering a variety of basic number-specific and general cognitive processing tasks to distinguish cognitive subtypes of MLD in primary education.

Knowledge of distinguishable subtypes is crucial to the development of custom-built interventions and the refinement of MLD definitions (Mazzocco & Myers, 2003; Wilson & Dehaene, 2007). Better understanding the nature of MLD is a prerequisite for the formulation of definitions detailing the specific cognitive mechanisms which are a positive indicator of MLD, instead of stating what a disorder is not (e.g. the IQ-discrepancy criteria) (Kavale & Forness, 2000; Stuebing et al., 2002).

1.1. Cognitive markers of MLD

Besides being based on a data-driven classification approach, definitions of learning difficulties subtypes should describe the cognitive processes impaired (King, Giess, & Lombardino, 2007; Skinner, 1981). Currently several cognitive processes have been frequently associated with MLD, but no comprehensive picture has emerged. The seemingly incompatible findings have led to the formulation of diverging theories (Andersson & Östergren, 2012; Szücs, Devine, Soltesz, Nobes, & Gabriel, 2013).

1.1.1. General cognitive processes

Initially, researchers focused on the relationship between MLD and general cognitive processes, e.g., working memory, but most of the examined general cognitive processes were not found to be related to MLD (Price & Ansari, 2012). Exceptions were children's working memory and intelligence (IQ), which were frequently, though not consistently, reported to be associated with MLD (e.g., Andersson & Lyxell, 2007; D'Amico & Guarnera, 2005).

To automatize mental calculations, humans are required to keep the problem in verbal working memory while they compute the answer in order to build long-term associations (Geary, 1993). Furthermore, researchers hypothesize that numbers are spatially coded (e.g., Dehaene, 1992) and therefore the processing of numbers is thought to be supported by visuo-spatial working memory skills. Numerous empirical studies comparing the working memory capacities of children with and without MLD reported deficits in visuo-spatial working memory, but not verbal working memory among children with MLD (D'Amico & Guarnera, 2005; McLean & Hitch, 1999; Passolunghi & Mammarella, 2010; Szücs, Devine, et al., 2013). Nonetheless, other studies did find verbal working memory deficits in MLD children (Andersson & Lyxell, 2007; Geary, Hoard, Byrd-Craven, Nugent, & Numtee, 2007; Kyttälä, Aunio, & Hautamäki, 2010; Rosselli, Matute, Pinto, & Ardila, 2010). To date, there is no satisfactory explanation which can account for these inconsistent findings. It is possible that deficient working memory capacities do not underlie severe calculation problems in all MLD children (Rousselle & Noël, 2007) and hence, the conflicting findings are attributable to the use of divergent MLD samples across studies. Data-driven classification studies could shed light on these inconsistent patterns of data by examining whether cognitive processing profiles with and without working memory weaknesses can be delineated in a sample of MLD children.

As noted by Geary (2011), children's IQ level should not be ignored when trying to explain MLD. It has been often associated with inter-individual differences in mathematics achievement and growth (e.g., Primi, Ferrão, & Almeida, 2010). Yet, contrasting the mathematics achievement of typically achieving children and children with MLD, Geary (2011) found that after controlling for IQ, the achievement gap disappeared for children having a low IQ, but remained for children having