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Identification of children with mathematics learning disabilities (MLDs) using latent class growth analysis

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ABSTRACT

The traditional way of identifying children with mathematics learning disabilities (MLDs) using the low-achievement method with one-off assessment suffers from several limitations (e.g., arbitrary cutoff, measurement error, lacking consideration of growth). The present study attempted to identify children with MLD using the latent growth modelling approach, which minimizes the above potential problems. Two hundred and ten Chinese-speaking children were classified into five classes based on their arithmetic performance over 3 years. Their performance on various number-related cognitive measures was also assessed. A potential MLD class was identified, which demonstrated poor achievement over the 3 years and showed smaller improvement over time compared with the average-achieving class. This class had deficits in all number-related cognitive skills, hence supporting the number sense deficit hypothesis. On the other hand, another low-achieving class, which showed little improvement in arithmetic skills over time, was also identified. This class had an average cognitive profile but a low SES. Interventions should be provided to both low-achieving classes according to their needs.

1. Introduction

1.1. *What is mathematics learning disability (MLD)?*

Mathematics learning disability (MLD), or developmental dyscalculia (DD), has been traditionally described as a disorder of arithmetic skills that reflects a discrepancy between one's low arithmetical abilities compared with his/her overall intelligence level and chronological age (Mazzocco & Räsänen, 2013). Approximately 7% of the population suffer from this disability (Shalev, 2007). Although numeracy skills are found to influence a person's educational, financial, and even health status to a similar extent as reading skills (Parsons & Bynner, 2005), there are far fewer research studies on MLD than on reading disabilities (Bishop, 2010; Gersten, Clarke, & Mazzocco, 2007). Because of the limited studies carried out on MLD, there is little consensus on the definition (Kaufmann et al., 2013) and the cognitive profiles of children with MLD (Mazzocco, 2007).

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1.2. The low-achievement method

Previously, the majority of the studies on MLD employed the low-achievement method of identifying children with MLD (e.g., Mazzocco & Thompson, 2005; Ostad, 1997; Passolunghi & Siegel, 2001). Children are identified as having MLD if their mathematics achievement scores below a certain percentile while their intellectual functioning falls within the normal range. However, there is a large variation in the cutoff values used in different MLD studies. A recent study summarized the latest MLD studies and found that the cutoff values employed in different studies ranged from the 5th to the 45th percentile on standardized mathematics achievement tests (Murphy, Mazzocco, Hanich, & Early, 2007). Clearly, with such a huge discrepancy in the cutoff values used, these studies usually identify different groups of children. It has been shown that the use of different cutoff values results in different cognitive profiles of the MLD samples identified (Murphy et al., 2007). The resulting inconsistency may hinder us from understanding the cognitive profiles of children with MLD.

To minimize the effect of the different cutoff values used, most recent studies used the tripartite method and identified three groups of children according to their mathematics achievement (e.g., Cowan & Powell, 2014; De Smedt & Gilmore, 2011; Geary, Bailey, & Hoard, 2009; Mazzocco, Feigenson, & Halberda, 2011b; Murphy et al., 2007). Children who show the most severe deficits in mathematics (e.g., lowest 10th percentile or 1.5 S.D. below the mean) are identified as MLD, while those who show milder deficits in mathematics (e.g., between the 11th and 25th percentile or between 1 to 1.5 S.D. below the mean) are identified as low-achieving (LA). The cognitive profiles of these two groups are then compared with their normally achieving (NA) peers. Studies using the tripartite method usually found significant differences in cognitive profiles between the MLD group and the other two groups (e.g., Cowan & Powell, 2014; Mazzocco, Feigenson, & Halberda, 2011a; Mazzocco et al., 2011b; Murphy et al., 2007). With more stringent criteria set for the MLD group, we can be more confident that the MLD group identified represents the true MLD population instead of containing some children who only have a mild degree of difficulties. The chance of having false positives is reduced.

Although the low achievement method (with either one or two cutoff values) has been used in most of the studies on MLD, there are several limitations that come along with this method. First, the cutoff values involved in the low-achievement model are arbitrary. These cutoff values may be used because they have been commonly used in previous studies instead of because they reflect something truly meaningful. A more important concern is that, as mentioned above, there is a huge range of cutoff values used in previous studies, and this variation results in different samples of MLD children identified (Murphy et al., 2007). Although the use of the tripartite approach has improved the situation slightly by identifying children with different degrees of difficulties, the issue of arbitrariness is not eliminated. It is possible that children within one group may be more different than the children who score around the cutoff boundaries but are classified into different groups. The use of an arbitrary cutoff in identifying children with MLD therefore warrants concerns.

Second, when using the low-achievement method, some studies made the classification based on information from a single time point (e.g., Chan & Ho, 2010; De Smedt & Gilmore, 2011; Landerl, Fussenegger, Moll, & Willburger, 2009). The use of information from a single time point is also problematic because of both the measurement error as well as the lack of consideration of children's learning process. Due to measurement error, children who score around the cutoff value may be classified as MLD in one time point while not in the other time point. In Mazzocco and Myers's (2003) study, for example, approximately 30% of the children being identified as MLD in one grade were no longer identified as MLD in another grade. Classifying children as MLD based on a one-off assessment therefore results in substantial classification error.

The lack of consideration of the learning process is another issue due to the classification of MLD with data from a single time point. According to the Response-to-Intervention (RTI) approach of identifying learning disabilities, students who are at risk for learning disabilities are those who are not able to learn at a reasonable rate and are unresponsive to suitable interventions (Fletcher, Coulter, Reschly, & Vaughn, 2004). The rate of learning is therefore an important piece of information in identifying learning disabilities that cannot be measured by any measurement from a single time point. Two previous studies suggest the importance of incorporating growth in the identification of children with learning disabilities. In Morgan, Farkas, and Wu's (2009) study, for example, children who had persistent mathematics difficulties in kindergarten showed a slower growth rate in mathematics in elementary school and were more likely to be identified as having MLD in elementary school compared with those who showed only transient difficulties or no difficulties. Having persistent difficulties in mathematics in kindergarten implies that these children have slow initial growth in mathematics, thus suggesting the importance of growth in predicting later outcome. Evidence also comes from the field of reading. For example, in a group of kindergarteners who participated in a kindergarten phonemic intervention programme, those who turned out to be children with dyslexia later on were found to require a longer time to master the phonemic knowledge taught in the programme. On top of that, the number of sessions required for a child to master phonemic skills outperformed the child's post-intervention phonemic skills in predicting their reading level at later ages (Byrne, Fielding-Barnsley, & Ashley, 2000). The usual practice of identifying children with MLD based on the assessment results from a single time point, which ignores the development of skills with time, therefore warrants cautions.

1.3. The latent class growth analysis

In light of the above limitations of the traditional approach (i.e., arbitrary cutoff, measurement error, lacking consideration of growth), a new latent growth modelling approach of identifying children with learning disabilities has