Identifying Learning Disabilities through a Cognitive Deficit Framework

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Abstract

Traditionally, students with Learning Disabilities (LD) have been identified using an aptitude-achievement discrepancy or response to intervention approach. As profiles of the cognitive deficits of discrepancy-defined students with LD have already been developed using these approaches, these deficits can in turn be used to identify LD using the discrepancy approach as a benchmark for convergent validity. Australian Grade 3 (N=172) students were administered cognitive processing tests to ascertain whether scores in these tests could accurately allocate students into discrepancy-defined groups using discriminant function analysis. Results showed that 77-82% of students could be correctly allocated into LD, low achievement and regular achievement groups using only measures of phonological processing, rapid naming and verbal memory. Furthermore verbal memory deficits were found, along with phonological processing and rapid naming deficits in students that would be designated as low achieving by the discrepancy method. Because a significant discrepancy or lack of response to intervention is due to cognitive deficits rather than the other way around, it is argued that LD should be identified via cognitive deficits.

Introduction

Although cognitive processing deficits often form part of the definition of Learning Disabilities (LD), they are rarely utilised in methods of identification (Kavale, Holdnack, & Mostert, 2005). The discrepancy method of identification is used to identify students with a significant discrepancy between aptitude and achievement (eg., Berk, 1983; Ferrer, Shaywitz, Holahan, Marchione, & Shaywitz, 2010). The validation of the discrepancy method of LD identification is often sought by subsequently testing the cognitive processing deficits of the students identified. In this study, the reverse of this approach is also considered so that the convergent validity of a method of identification based on cognitive processing deficits is assessed using the discrepancy method of identification. It should be noted that in the current study LD refers to reading disabilities specifically.

LD is defined as "specific patterns (subtypes) of neuropsychological assets and deficits that eventuate in specific patterns of formal (e.g., academic) and informal (e.g., social) learning assets and deficits" (Rourke, 2005, p. 111). It is well documented that LD is a heterogeneous disorder that involves intra-individual cognitive deficits, presumably of a neurological basis (Scruggs & Mastropieri, 2002). Despite this, the two most common operationalisations of LD are the discrepancy method or Response to Intervention (RTI). RTI operationalises LD as a failure to sufficiently respond to repeated intervention (Fletcher, Francis, Morris & Lyon, 2005). In the traditional discrepancy method a student with a significantly higher aptitude than achievement is designated LD; in the regression-adjusted discrepancy method this difference between the two test scores is adjusted to account for regression to the mean. This discrepancy is used to separate students with LD from students who do not have LD but are Low Achieving (LA) poor readers.

In a study of the opinions of LD academics, 96 and 88 percent of respondents did not believe that RTI and discrepancy, respectively, were sufficient for LD identification (Hale et al., 2010). Others are concerned that the rise of RTI and concurrent decrease in the use of cognitive processing measures could result in a phasing out of the concept of LD altogether (Mastropieri & Scruggs, 2006).

While there has been an ongoing debate about the relative benefits of discrepancy and RTI, both of these methods of identification are ultimately identifying likely secondary outcomes of LD, rather than detecting components of the actual disorder. In the case of RTI, this secondary outcome is a failure to respond to repeated intervention and in the discrepancy method this is a significant difference between aptitude and achievement. There are of course a number of plausible explanations for both of these outcomes which is why both have exclusionary criterion such as cultural disadvantage. Both discrepancy and RTI seem susceptible to socio-economic bias, with the discrepancy method overlooking those with cultural disadvantage (Brooks-Gunn et al., 1996) and RTI over-identifying the same cohort (Al Otaiba & Fuchs, 2006). By basing operationalisation of LD on definable and easily tested cognitive deficits, many of the political issues that influence current LD identification (McPhail & Palincsar, 1998) may be avoided.

There is a need, especially in Australia, for identification methods that assess cognitive deficits inherent to LD (Skues & Cunningham, 2011). More direct identification paradigms, such as the double deficit theory, are advantageous as the cognitive deficits thought to be responsible for LD are directly assessed. The double deficit theory states that naming speed and phonological processing deficits are the underlying causes of LD (Wolf & Bowers, 1999). This method received support in the literature, including research that supports the idea that phonological processing (Muter & Snowling, 2009; Puolakanaho, Poikkeus, Ahonen, Tolvanen, & Lyytinen, 2004) and naming speed (Wolf, Bowers, & Biddle, 2000) are longitudinal predictors of LD and reading achievement.

Verbal memory is another cognitive process related to LD worthy of further scrutiny. In particular, verbal memory in relation to IQ should be taken into account in any LD research utilising the discrepancy method of identification. This is because working memory, linked with verbal memory is thought to affect both crystallised and fluid intelligence (Swanson, 2008) and can also be well predicted by g, or latent intelligence, in a structural equation model (Colom, Rebollo, Palacios, Juan-Espinosa, & Kyllonen, 2004). Therefore if g, the concept that IQ was developed to measure, is strongly correlated with working memory, and shares properties with verbal memory, then students with deficits in verbal memory would have a reduced IQ score. This reduced IQ could decrease the probability of a student receiving an LD diagnosis via the discrepancy method of identification (Siegel, 1989).

If this theory is considered in conjunction with the finding that students with LD and LA have similar deficits in phonological processing and naming speed (Ellis, McDougall, & Monk, 1996), then it is possible some students in the LA cohort may actually have LD as well, but with an additional verbal memory deficit that reduces their measured IQ. It is possible that phonological processing and naming speed deficits are better predictors of a significant discrepancy between aptitude and achievement than other cognitive deficits. In addition, there may be students who have other deficits, like verbal memory, that wrongly exclude them from discrepancy based identification and as such have received more attention in the literature.

Ultimately, the primary aim of developing a more accurate LD identification paradigm is so that more effective remediation can be facilitated. It is vital that groups of students are identified correctly so that appropriate remediation for these groups can be developed (Wodrich, Pfeiffer, & Landau, 2008). This aim causes difficulty in LD research as students with LD make up such a diverse cohort. Specific LD phenotypes based on cognitive processing, such as the phonological processing and short term memory deficit phenotype (Bonifacci & Snowling, 2008), have been put forward. The development of these phenotypes could facilitate more accurately targeted remediation.

Multiple deficit models that could be used to identify these phenotypes have been developed such as the multiple deficit hypothesis (Ho, Chan, Tsang, & Lee, 2002) where naming speed, visual, phonological and orthographic deficits are used to identify LD. Another model put forward, the cognitive hypothesis testing model, used a wide number of processes to identify LD within an RTI paradigm (Fiorello, Hale, & Snyder, 2006). A triple deficit model with phonological, orthographic and naming speed deficits has also been put forward (Badian, 1997; Stage, Abbott, Jenkins, & Berninger, 2003). Recently, a study found that students with LD have phonological, Rapid Automatic Naming (RAN), short-term memory and working memory deficits (Aguilar-Vafaie, Safarpour, Khosrojavid & Afruz, 2012). The current study will be conducted on a similar premise to these studies; the three cognitive processes to be examined in this study are phonological processing, naming speed and verbal memory.

The aim of this study is to use Discriminant Function Analysis (DFA) to determine whether cognitive variables (phonological processing, naming speed and verbal memory), alone, can predict the groupings of students based on their aptitude and reading achievement scores. A secondary aim of the analysis is to illuminate some of the cognitive processing differences between discrepancy defined students with LD and LA. This is because the DFA will be used to predict membership in groups conceptually aligned with the discrepancy model of LD, using cognitive variables that are thought to contribute to LD. Both LD and LA groups consist of poor readers but what cognitive deficits, if any, separate the two groups warrants investigation. The first hypothesis is that cognitive processes will be able to predict, with better accuracy than would be expected by chance, the presence of LD as dictated by both traditional and regression-adjusted discrepancy methods. The second hypothesis is that verbal memory will play a similar role in identification of LD as naming speed and phonological deficits, and as such will differentiate between students with LD and LA.

Method

Participants

Five schools participated in the study; four of these schools were Public Schools in the outer eastern suburbs of Melbourne, Australia, and one Catholic Primary School in the south-eastern suburbs. In each school, all Grade 3 students were invited to participate and 175 agreed (56.45% response rate). Results from three students were excluded on the basis of having English as a second language or disability unrelated to LD. Of the remaining 172 students, nine did not complete one or both of the tests required to ascertain their discrepancy defined LD status and were excluded from all analyses. Therefore 163 Grade 3 students (M = 8.83 years, SD = 0.42 years) participated. The number of Grade 3 participants, mean age and response rates from each school, in chronological order of testing, is shown in Table 1. Although the response rates were different from school to school, intra class correlations were run to ensure that school was not responsible for more than 5% of the variation in scores, and as it was not, this was not deemed a significant concern.

Measures

Progressive Achievement Test in Reading

The Progressive Achievement Test in Reading (PAT-R), 4th Edition (Australian Council for Educational Research (ACER), 2008), is a widely used and validated Australian test of reading comprehension. The group administered test has a multiple choice format and each level of the test can cater to three consecutive academic years at school. Students are given 40 minutes to complete the test as well as approximately 15 minutes administration time. Students in the current study were administered either the Grade 2 or 3 PAT-R by a researcher or their classroom teacher. As each grade level has its own norms in each test, percentile scores are comparable across grades (ACER, 2008). The PAT-R is widely recognised as psychometrically sound, with reliability ranging from .88 to .90 (ACER, 2008). Furthermore, validity is supported by correlations ranging from .65 to .86 between the PAT-R and other tests of reading comprehension (ACER, 2008).

Raven's Progressive Matrices

The Raven's Progressive Matrices (RPM; Raven, Styles & Raven, 1998) was used to assess aptitude as per the aptitude/achievement discrepancy paradigm. The RPM consists of 60 multiple choice items where students are asked to select the missing piece of a larger pattern. These 60 questions are divided into five sets of increasing difficulty. The RPM examines non-verbal reasoning in a manner that does not need any reading or language comprehension, as there are concerns that measures of intelligence that include such measures do not provide a suitable juxtaposition to tests of reading ability when looking for a discrepancy between aptitude and achievement (Stanovich, 1991). Furthermore the RPM can be administered to an entire group, a more readily applicable classroom scenario. The test has a multiple choice format and can be group administered to an entire class. The test has good internal consistency with Cronbach's alpha reported between .68-.98. The majority of studies comparing the RPM to other tests of cognitive validity find convergent validity of .70 or above (Raven, Court & Raven, 2003).

As per the administration manual, raw scores are transformed into norm scores based on age groups. RPM norms are given in percentile groups of 5, 10, 25, 50, 75, 90 and 95th percentiles. This presented an issue, as these percentile groups provided little discrimination for those between the 25th and 75th percentile. Therefore, raw scores were used in the current study.

Nonword reading list

A list of 20 nonwords (Callinan, 2011) was used to measure phonological processing, developed as part of larger study. Nonwords are made up pronounceable words with no meaning; for instance *blurk* is a nonword, *thdfaxc* is not. Some of these words had more than one correct pronunciation based on letter sounds and precedent in commonly used English words, for instance *kour* could be pronounced to rhyme with *four*, *tour* or *hour*. Examples of the nonwords in the test include *yex, joid* and *lantople.* The mean score for the scale was 13.09 (*SD* = 4.97) out of a possible score of 20.

Students were presented with a folder with six words in very large font per page. They were asked to attempt to read all the words out loud. They were allowed to pass words, however if they started passing whole pages they were asked to check each word on that page to make sure that there were not some words on each page that they could read. Scores consisted of the number of the 20 words in the list that the student read correctly. The test has been psychometrically validated for this sample using item response theory and has a Cronbach's alpha of .89 and a test-retest reliability of .86 (Callinan, 2011).

Rapid Automatic Naming

Students were given a laminated sheet of paper with five colours repeated in random order over 48 (6x8) blocks of colour. There were ten occurrences of three of the colours and nine occurrences of the other two. Students were asked to read the colours out loud, left to right, line by line, as fast as they could. Their responses were initially on a digital audio recorder and translated to times at a later date. The same approach was then repeated, using the letters, B, O, M, E and R that were once again repeated in random order for 48 letters. Timing started for students' attempts at both RAN tasks from the moment that each student completed the first colour or letter and ended when they finished the last one. Scores in the RAN tests were obtained by measuring the time taken to read the colours or letters in whole seconds. While internal consistency cannot be assessed on these single item scales, test-retest reliability for both the colour, $r(29) = .87$, $p < .001$, and letter, $r(29) = .83$, $p < .001$, RAN tests was good.

Digit span

Digit span tests, both forward and backward (DSF & DSB), are often used as a measure of verbal memory (e.g., Pisoni, Kronenberger, Roman & Geers, 2011; Reppermund, Ising, Lucae & Zihl, 2009). DSF is a widely accepted measure of short term memory, but the role of DSB is unclear with some studies utilising it as a measure of short term memory (Richardson, 2007) and some as a measure of working memory (Süß, Oberauer, Wittman, Wilhelm & Schulze, 2002). What is more widely accepted is that both tests tap into a verbal memory construct relevant to studies on LD (Bopp & Verhaeghen, 2005).

Students were administered both digit span forward and backward (DSF & DSB) tests. Numbers were placed into sets, three of each digit length; two digits to nine digits for the forward span, and two to eight digits for the backwards span. These were then printed on scoring sheets for easy administration. These sheets were filled out by the test administrator as the test consisted of verbal questions and responses. If a student got all three attempts at a given digit string length incorrect, then the testing was stopped. This process was then repeated for the backward digit span. The longest digit string that the student was able to recall for the forward and backward tests was noted as their score.

The digit span test has established good test-retest reliability (Flanagan & Kaufman, 2004; Gray, 2003; Karpicke & Pisoni, 2000). Although there is significant overlap between the DSF and DSB, there is thought to be some cognitive processes exclusive to each (Reynolds, 1997). Therefore the two tests were assessed as separate variables.

Procedure

The first test to be administered to participants was the RPM. From this point the order of administration varied, dependent on a number of factors. Firstly, some schools administered the PAT-R before the researcher started testing and this impacted on the order of administration. The mean PAT-R score from students tested in first semester (M = 50.98, SD = 23.99) was not significantly different to the scores of students tested in second semester (M = 53.66, SD = 27.09), $t(161) = -0.56$, $p > .05$). Secondly, the timing of the group testing was much more important to the classroom teachers than the timing of the individual testing. Therefore, in a given classroom, some students were administered the individual tests before the PAT-R, and others completed the individual tests after the PAT-R.

The administration order for the individual tests remained consistent throughout testing. The working memory test was administered first, the RAN test second and the nonword list last. Although the exact timing of administration was not recorded, anecdotally, individual testing took anywhere from 5 to 25 minutes depending on the student, with the majority of students taking between 10 and 15 minutes.

Data Analysis

Once students are grouped into LD, LA or RA groupings based on traditional or regression adjusted discrepancy guidelines, DFA was used to predict group membership based on only scores from nonword reading, rapid naming and verbal memory scores. Analyses were computed from group sizes as these were uneven both in the sample and in the general population.

The group sample sizes are expected to exceed the recommended minimum cell size number of exceeding the number of predictor variables (Tabachnick & Fidell, 2007). However, given that the numbers of students allocated to the LA and LD groupings are likely to be less than 20, and the group sizes are unequal, the tests are less robust to violations of assumptions underlying the tests. Hence, initially the significance of Box's M will be checked with regards to equality of the variance-covariance matrices. If this test is not significant, then the analysis is considered to be robust (Spicer, 2005). In the event that Box's M is significant, the variances and covariances will be inspected and, provided that the variances and covariances of the larger group generally exceed those of the smaller groups, then findings are reliable (Tabachnick & Fidell, 2007). If these conditions are not met, results from analyses will be tentative at best.

With the new allocation into the three groups from the DFA analysis, the differences in test scores were analysed using a series of one-way ANOVAs. In order to further investigate the significant differences in test scores amongst the DFA groups without compromising Type I error, planned contrasts will be used.

Results

There was no missing data in this study as the nine students who missed one of the established tests were excluded and all other participating students completed all the other tests. In order to measure the relative importance of the different variables all scores were converted to *z*-scores for subsequent analyses. For ease of interpretation, the two RAN tests *z*-scores were multiplied by -1 so that high scores indicate strength in that test, and could therefore be interpreted in the same manner as all the other *z*-scores used in the study.

Traditional discrepancy

The first step in analysing how well students can be allocated into traditional discrepancy groups by cognitive processing variables is to ascertain which students will fall into these traditional discrepancy-defined groups. Students who had a *z*-score on the PAT-R one or more standard deviations below their *z*-score on the RPM were designated LD. Any students who were more than one standard deviation below the mean in reading and who did not fit the LD criterion, were designated LA. All remaining students were placed into the Regular Achievement (RA) group. Using this method of identification, 27 (17%) students were flagged as belonging in the LD group. The numbers for LA identification are a little lower than LD with 19 (12%) students. The remaining 117 students (72%) were allocated into the RA group.

Discriminant Function Analysis

This DFA was run to predict discrepancy dictated groupings using nonword reading, DSF, DSB and colour and letter naming speed tests as predictor variables. The percentage of students that would be correctly allocated in each analysis by chance is calculated for each DFA as per the method outlined by Tabachnik and Fidell (2007). Results from Box's M indicated that the data was suitable for a DFA, $F(9,30) = 1.44$, $p > .05$. Two discriminant functions were calculated. Although the second function on its own was not significant (χ^2 (4) = 8.04, $p > .05$), the two functions combined were significant (χ^2 (10) = 45.01, $p < .001$). The first discriminant function, responsible for 84% of the variance in the model, differentiated between the RA group and the combined LD and LA groups, and the second function, responsible for the remaining 16% of the variance in the model, differentiated between the LD and LA groups. The standardised structure loading matrix of the discriminant functions is shown in Table 2. The best predictors for distinguishing between RA and LD were the nonword test, LRAN and DSF. The DSF and DSB were the best predictors for distinguishing students with LD and LA. Seventy-seven percent of cases were correctly classified compared to the 56% expected to be correctly allocated by chance alone. The subsequent classification of students into the RA, LD and LA groups is shown in Table 3. As can be seen in Table 3 there were still a sizable number of false negatives and positives. The majority of these are students who would have been placed in LD or LA groups through the discrepancy method that do not have the cognitive deficits that would be expected in a student who had LD or even LA.

Traditional discrepancy discriminant function analysis: Comparison of groups

A series of one-way ANOVAs (Bonferroni-adjusted alpha = .007) was conducted to ascertain the differences in test scores between the groups identified through the DFA. The means and standard deviations for the three DFA groups, along with the results from the ANOVAs, are shown in Table 4. Significant differences in means were found between the LD, LA and RA groups on all tests accept the DSB, colour RAN and the RPM. The RA group had the highest mean for all of the variables except for non-significant differences in backwards digit span and RPM. The LA group had the lowest mean in all of the variables except for non-significant differences in colour RAN, in which the LD group had the lowest mean.

In order to further investigate the significant differences in test scores amongst the DFA groups without compromising Type I error, planned contrasts were utilised. The first contrast compared the RA group to the LD and LA groups and the second contrast compared the LD and LA groups. The results from the two planned contrast are shown in Table 5. There were significant differences between the RA readers and the combined LD and LA group with the RA readers scoring better on the nonword reading, DSF, letter RAN and the PAT-R. Interestingly, the DSF was the only test with a significant difference between the LD and LA groups, with the LD group performing significantly better than the LA group on this test.

Regression-adjusted discrepancy

Students were also grouped as per the tenets of regression-adjusted discrepancy so that the results of the current study can be compared to studies using both types of discrepancy. The correlation between the RPM and the PAT-R, representing aptitude and achievement, is .42 ($p < .001$). Consequently, if the difference between the RPM *z*-score multiplied by .42 and the z-score of the PAT-R is more than one, a student was identified as LD. If students had a reading level one standard deviation or more below the mean on the PAT-R, but were not in the LD group, they were designated LA. All students not designated as LD or LA were placed in the RA group.

Many students remain in the same group irrespective of the selected method of identification. The primary difference lies in the LD identification: high IQ students are more likely to be considered LD via the traditional method and more likely to be considered RA via the regression-adjusted method. Furthermore, low IQ students are more likely to be considered LA via the traditional method and LD via the regression-adjusted method. Although the actual number of students with LD identified via the regression-adjusted method remained steady at 28 (17%), the number of LA students identified was reduced to 10 (6%, compared to 12% in the traditional discrepancy method) due to the change in the allocation methods. Finally, there were 125 students (77% compared to 72% in the traditional discrepancy method) identified as RA in the regression-adjusted discrepancy model.

In this section the same analyses that were performed in the traditional discrepancy DFA section were repeated. Consistent with the previous DFA, the smallest cell size was larger than the number of predictor variables (Tabachnik & Fidell, 2007), which were once again nonwords, colour and letter RAN, DSF and DSB, so the sample size was sufficient for the analysis. Box's M for the regression-adjusted DFA was significant, $F(30,9) = 1.85$, $p = .004$. An inspection of the variance-covariance matrices for the three groups found that the variances for the nonword and DSF scores for the RA group, the largest group, exceeded the variances on these measures in the LD and LA groups. Furthermore the covariances on the five measures were fairly similar between groups, therefore it was considered robust enough for DFA, albeit interpreted with caution.

Two discriminant functions were calculated and, although the second function was not significant after removal of the first function (χ^2 (4) = 0.55, $p > .05$), the two functions combined were significant (χ^2 (10) = 49.34, $p < .001$). The loading matrix of the discriminant functions is shown in Table 6. The first function, that seemed to discriminate between the RA and combined LD and LA groups, was responsible for 99% of the variance in the model and had high loadings for the nonword, DSF and LRAN tests. The second function, responsible for only 1% of the variance in the model, was based on the two RAN tests and attempted to differentiate between the LD and LA groups.

The classification of students into the LD, LA and RA groups is shown in Table 7. The DFA was not able to predict membership into the LA group using the cognitive variables provided. Despite this, 82% of students were correctly classified compared to the 63% that would have been allocated correctly by chance.

Regression-adjusted DFA: Comparison of groups

Because only two groups were identified through the DFA predicting membership in the regression-adjusted groups, independent *t*-tests were conducted to ascertain the differences between these groups. The means, standard deviations and the results of the *t*-tests on all of the variables for the two groups identified by the DFA are shown in Table 8. Significant differences between all tests except for the CRAN and RPM were found. In all of the tests, the RA group scored higher than the LD group. That significant differences were found in means between the groups on the majority of tests is not surprising as all of these tests were utilised in making up the groups. The only exception to this was the RPM, one of two factors utilised to discriminate between the groups for the outcome variable, was not significantly different between the two predicted groups.

Discussion

The aim of the current study was to ascertain how well cognitive deficits could predict membership in discrepancy defined LD, LA or RA groups. As per the first hypothesis of this paper, the DFA indicated that discrepancy identified LD groups could be identified through the use of tests of cognitive processing, with better accuracy than would be expected by chance. The second hypothesis, that verbal memory deficits would play a similar role in the prediction of discrepancy defined groups was also supported. The digit span forward test was a similar predictor to the letter RAN and nonword tests as a differentiator between Students with LD and LA and RA students. In addition it was the only test score that, on average, was significantly different between the LD and LA groups in the DFA allocated traditional discrepancy model with students with LD scoring higher.

Cognitive processes were successful predictors of both traditional and regression-adjusted discrepancy group membership. This is in line with other cognitive processing models used to identify LD (Aguilar-Vafaie, 2012; Badian, 1997; Fiorello et al., 2006; Ho et al., 2002; Stage et al., 2003; Wolf & Bowers, 1999). Phonological processing, naming speed and verbal memory could successfully predict 77% of students into their traditional discrepancy-defined groups, as compared to the 56% that would be expected by chance. Furthermore, these same processes could successfully allocate 82% of students into regression-adjusted discrepancy-defined groups, despite no LA students being identified via this method. This is compared to the 63% rate that would be expected from chance alone. This is an important finding given that other studies have found a correspondence between methods of LD identification of 48-70% (Proctor & Prevatt, 2003).

Support was found in the current study for the contention that some students with LD may not be identified through the discrepancy paradigm if they also have verbal memory deficits (Siegel, 1989). In the traditional discrepancy DFA model, Students with LD and LA had similar deficits in phonological processing and RAN but LA students also had memory deficits. This provides an explanation as to why naming speed and phonological processing differences were often not found between discrepancy defined students with LD and LA in some studies (e.g., Ellis et al., 1996). It could be that there are students with LD in both groups with the students with LD in the LA group having verbal memory deficits that affect both their reading and nonverbal IQ. As working memory plays a role in IQ (Swanson, 2008), these students would be less likely to be identified as LD within a discrepancy paradigm as their verbal memory deficits are likely to reduce their IQ scores. However, these students are just as likely as their discrepancy-defined LD counterparts to have phonological and naming speed deficits. Therefore, any students in either group that have these deficits should be identified as potentially LD and both groups require similar assistance and remediation.

The finding that LA students have digit span deficits on top of the same deficits as students with LD highlights the major problem facing both the discrepancy and RTI methods of LD identification. Both methods are based on identifying a possible outcome of having LD rather than a cause. LD is not caused by a significant discrepancy between aptitude and achievement, nor is it caused by a lack of response to intervention. Furthermore, there is nothing to say that either of these markers are necessary outcomes of having LD. Therefore much of the research in this field is based on those students who either have a significant discrepancy or failure to respond to intervention that may in turn be symptomatic of LD. Therefore it is important when investigating the cognitive deficits inherent to LD that the possibility that some of the cognitive deficits that are responsible for LD do not fit well into the existing popular methods of identifying LD. So if for instance, verbal memory deficits do play a role in LD, it is more important that these deficits are indicative of having a neurological and lasting disorder than that it is that they predict the likelihood of having a significant discrepancy or a failure to respond to intervention.

The thorny issue of different types of memory and their operationalisation was outside the scope of the current study. However, investigation of memory issues in LD identification warrants further investigation. The best memory test for predicting reading achievement, and whether that test will be assessing working memory or short term memory, is currently unclear. The current study utilised digit span as a measure of verbal memory due to its common use in the past, however this does not mean that it is the most appropriate measure. A further limitation in this study is that of sample size. By using a general sample, as compared to an LD-specific one, it was possible to administer a test to the same population it would be administered to in theory. However this also meant that there were few LD and LA students. While the data were checked for robustness for the analyses, some caution is warranted in extrapolating the results to the whole population, particularly in the analysis on regression-adjusted discrepancy groups. What is needed is replication of these results in an independent sample.

This brings us to the most important caveat and suggestion for future research from this study. Other cognitive processes may be important in the identification of LD. The role of orthographic processing deficits in LD is unclear, and other processes are still being studied as possibly contributing to LD. For instance, recent research suggests that morphological processing may play an important role in literacy development (Apel, Wilson-Fowler, Brimo & Perrin, 2012). Therefore, there may be other deficits that contribute to LD and the inclusion of these deficits into a model such as this one could result in better accuracy.

Previous methods of LD identification have been accused of failing to sufficiently inform remediation strategies (Wodrich et al., 2008). However, unless decades of research is to be discarded, examining how these deficits can help explain the well documented strengths and weaknesses of the discrepancy method is important. Then more accurate methods can be developed to identify different groups of students who have LD. If relatively homogenous sub-groups of students with LD can be identified based on cognitive deficits, research on appropriate remediation programs would be made simpler and more direct, thus benefiting the students who most need this assistance.

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