Early Identification of Dyslexia

Current Advancements and Future Directions

by Hugh W. Catts and Yaacov Petscher

Early identification is an essential component of an effective intervention program for developmental dyslexia. Research demonstrates that children who are at risk for dyslexia have better outcomes when identified early and provided with appropriate intervention (Wanzek & Vaughn, 2007). Despite the importance of early identification, there are significant challenges to carrying it out. Whereas current procedures are successful in identifying many children who are at risk, these procedures are often associated with high false-positive rates. This over-identification can be costly and lead to many children receiving unnecessary intervention. There are also other challenges concerning the implementation of early identification programs; that is, who will do the assessment, when will it be done, how to get children engaged, and how much time can be devoted to assessment. In this article, we will briefly discuss recent advancements in theory, measurement, and technology that can help address some of the challenges faced in the early identification of dyslexia.

Multifactorial Assessment

Dyslexia is a complex developmental disorder involving genetic, neurological, and environmental factors. Early models focused primarily on single deficits as causal factors of dyslexia. Primary among them has been the phonological core deficit model (Stanovich, 1988). This model argues that deficits in phonological (speech sounds) processing, specifically phonological awareness, leads to a cascade of difficulties in learning to decode and recognize printed words. Numerous studies have examined the link between dyslexia and deficits in phonological processing and there is considerable support for a causal connection (Elliott & Grigorenko, 2014). Other single deficit accounts have focused on visual problems in individuals with dyslexia. Research indicates that some individuals with dyslexia do have visual deficits, but it remains unclear how much of a causal role these deficits play in dyslexia (Saksida et al., 2016).

Whereas single deficit models have received much attention, there is now clear evidence that they are not sufficient to account for dyslexia. For example, the relationship between phonological processing deficits and dyslexia is far from complete. Some children with dyslexia have no history of phonological deficits and many children with phonological deficits do not develop dyslexia (Catts, McIlraith, Bridges, & Nielsen, 2017; Pennington et al., 2012). Such evidence has led to the proposal of multiple causal deficit models of dyslexia (see Catts, 2017). These models argue that multiple genetic, neurological, and environmental factors interact to increase the risk of dyslexia. For example, oral language impairments, slowed speed of processing, and/or limited early literacy experiences can combine with phonological deficits to increase the probability of dyslexia. Haft, Myers, and Hoeft (2016) have also introduced the Compensatory Risk and Protection model that not only posits multiple risk factors but highlights the importance of protective factors. They argue that protective factors such as early intervention, growth mindset, and task-focused behavior can provide resilience and reduce the probability of dyslexia in at-risk children.

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The above work indicates that if procedures for early identification are to be accurate, they will need to be multifactorial and consider more than one or two factors during assessment. Other fields commonly use multiple factors to identify risk. For example, in medicine, practitioners have used multiple indicators to determine risk of cardiovascular disease. In fact, recently, a cardiovascular disease risk calculator has been introduced to assist in this identification. This online calculator uses data for nine variables to determine the probability of cardiovascular problems in the next 10 years. It can be completed by a practitioner during an office visit or is available to the public online. See *http://www.cvriskcalculator.com/*. An accompanying application also includes readily assessable reference information related to therapy, health monitoring, and lifestyle.

A comparable procedure could be adapted to assist in the early identification of dyslexia. In fact, a prototype of such a calculator was introduced by Catts, Fey, Zhang, and Tomblin (2001). This calculator used five kindergarten variables (phonological awareness, rapid naming, letter identification, sentence repetition, and mother's education) to estimate the probability of reading difficulties in second grade. While the accuracy of the calculator was limited, current science and technology could be leveraged to create a more accurate and useful

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Abbreviations

CAT: Computer adaptive testing

EARS: Earlier Assessment for Reading Success probability calculator for dyslexia. As in medicine, it could be used by both practitioners and public to identify dyslexia and provide information concerning further assessment and treatment.

Building on this idea, Petscher, Truckenmiller, and Zhou (2016) developed an automated, online risk calculator (i.e., the Earlier Assessment for Reading Success; EARS) that uses one or more curriculum-based measurements in K–3 to predict reading comprehension and language risk. Similar to the approach of Catts et al. (2001), the EARS estimates various probabilities of reading and language success based on available curriculum-based measures in K–3. For example, suppose Teacher A has a kindergarten student's fall and winter letter naming fluency scores, but Teacher B only has a winter letter naming fluency score for one of her students. Both teachers could use the EARS to enter their respective student's score(s) and both will receive a report that provides the student's probability of reading success at the end of kindergarten and grades 1–3. In other words, EARS is programmed to handle single and multivariate informed predictions concerning the likelihood of success.

One of the challenges to the use of multiple indicators is the time required to complete an assessment. Assessment time can increase significantly with each additional measure for an indicator. One approach that has proven to reduce the amount of time required for assessment is computer adaptive testing (CAT). Adaptive testing optimizes the assessment experience by creating individual forms of items for individual students. Traditional paper-and-pencil assessments typically involve one form of fixed items and are delivered to a set of individuals, such as students in a classroom. A problem with a set of fixed items is that item content can be too easy or too hard depending on the ability of the student. For students with reading problems, even the "easiest" items on a grade-level assessment can be challenging because they may not have knowledge commensurate with a typically achieving student. As a consequence, the resulting assessment score is an imprecise estimate of the student's actual knowledge; rather than the assessment showing what the student knows, it instead represents what they *do not* know, and the teacher is left with little actionable information about how to target instruction and intervention based on the student's supposed capabilities.

CATs attempt to circumvent this problem by creating custom-built forms for each individual student at the individual student's unique ability level. By leveraging a set of algorithms and estimating item and person features using item response theory psychometric models, a CAT can precisely calibrate a student's ability. More succinctly, CAT can be analogized to the childhood game of "hot and cold," where the CAT is seeking to find items that are close to the ability of the student (Mitchell, Truckenmiller, & Petscher, 2015). There are many commercially available CATs that can be used for screening and progress monitoring purposes (Shapiro & Gebhardt, 2012). CATs may be beneficial for dyslexia screening not only for their increased precision in skill estimation and time savings, but also for their ability to measure a breadth of content (e.g., word reading, language, and phonological memory) in a timeframe that has typically allowed for only one construct to be assessed (Petscher, Foorman, & Truckenmiller, 2017).

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Computer Assisted Technology

Another issue related to screening is how test items are delivered and scored. In most "pencil and paper" assessments, a teacher or aide provides instructions, delivers items, and scores responses. Such implementation takes time and relies on the fidelity and reliability of the examiner. With the development of technology, computer assisted devices can now provide instructions, present items, and score responses. Until recently, real time computer-based scoring has been limited to items in which the child selected the item/answer using touch screen technology. This has meant that these assessments could only be used to measure "receptive" abilities. However, advancements in speech recognition now allow for some computer-based scoring of children's spoken (expressive) responses. For example, Northwest Education Association recently introduced a new version of its Measures of Academic Progress reading fluency measure in which speech recognition software encodes children's reading of computer-presented passages and calculates words read correctly per minute. The software is specifically tailored to children 4–8 years of age and is sensitive to beginning readers' behaviors such as word and line skips, substitutions, and long pauses. This is an important advancement and similar software could be developed to record and score measures used in screening tests for dyslexia.

Gamification

In addition to considerations for how to more efficiently administer and score assessments, an emerging component of the assessment process is how to engage and enhance the user experience. One method for increasing the motivation and enjoyment of assessments is gamification, which is the use of gaming elements in non-game contexts (Deterding, Sicart, Nacke, O'Hara, & Dixon, 2011). Children are increasingly exposed to social media, interactive advertising and micro-transactions, and video games in general. As a result, researchers and practitioners have become interested in how gamification may be used in the assessment process as a means for improving motivation, effort, and overall satisfaction with an assessment experience (Hanus & Fox, 2015). Gaming has seemingly intuitive appeal. Rather than a student being situated within a typical didactic examiner-child environment with items statically delivered, the student could instead be immersed in a live, electronic platform with art, music, and audio that could bring an assessment to life. Gamification may be inclusive of basic environments that use animation to deliver item content in a unique, created world, or as advanced as including competitive games with rewards, trophies, and avatar customizations for the student. The research on gamification is mixed. In a study by Domínguez et al. (2013), participants who participated in an e-learning platform reported higher motivation and overall performance in the assessment but did worse on subsequent classroom assignments. Conversely, in a study of gaming and course feedback (Charles, Charles, McNeill, Bustard, & Black, 2011), the authors found that students who were given skill progress through gamification were more likely to enjoy the feedback and had higher rates of success compared to a control group.

Where gamification considerations have promise for holding student interest, researchers are quick to note that how a reward system is embedded should be carefully considered. Deci, Koestner, and Ryan (2001) have suggested that motivation may actually decrease in gamified environments when those who are already interested in learning shift their motivations from intrinsic (i.e., motivated to learn for themselves) to extrinsic (i.e., motivated for the reward) factors. Because many electronic games are based on reward systems, gamified assessment with rewards should be sensitive to the motivational profile of a student.

Where traditional screeners use short-window longitudinal data within one academic school year to create cut-points for the assessments, following students over multiple years and building out longitudinal risk models may be advantageous in capturing the students who are late-emerging in their reading difficulties.

Longitudinal Risk Models

A final consideration for future directions in early identification lies at the very heart of screening assessment itself, "What are we screening for?" A single screener is inherently composed of two assessments—the screener and the outcome. Outcomes can range from criterion-referenced tests, such as state achievement tests, to norm-referenced tests that include national norms for word reading and/or comprehension. Independent of the outcome type, virtually all screeners share a commonality in that they screen for risk at the end of the current grade level. This objective is a natural outcome for practitioners and educational researchers since the progression of student development easily can be tethered to end-of-year academic success. A limitation of calibrating screener cut-points to end-of-year performance is that a sizable percentage (40%) of students with word reading deficits may not be identified for the first time until after grade 2 (e.g., Catts, Compton, Tomblin, & Bridges, 2012). Where traditional screeners use short-window longitudinal data within one academic school year to create cut-points for the assessments, following students over multiple years and building out longitudinal risk models may be advantageous in capturing the students who are late-emerging in their reading difficulties. Additional progress monitoring assessments can further assist us in understanding the time course of these difficulties.

In this short article, we have highlighted recent developments or considerations that have the potential to improve the efficiency and accuracy of early identification of dyslexia. For these to have their maximum benefit, newly developed assessment tools will need to be matched with interventions that can address the full range of problems associated with dyslexia. Significant advancements are being made in the development of intervention programs for dyslexia (e.g., Lovett et al., 2017) and we are optimistic that these programs can be coupled with effective screening and progress monitoring tools.

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