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Predicting Individual Differences in Reading and Spelling Skill With Artificial Script–Based Letter–Speech Sound Training

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Abstract

In this study, we examined the learning of letter–speech sound correspondences within an artificial script and performed an experimental analysis of letter–speech sound learning among dyslexic and normal readers vis-à-vis phonological awareness, rapid automatized naming, reading, and spelling. Participants were provided with 20 min of training aimed at learning eight new basic letter–speech sound correspondences, followed by a short assessment of mastery of the correspondences and word-reading ability in this unfamiliar script. Our results demonstrated that brief training is moderately successful in differentiating dyslexic readers from normal readers in their ability to learn letter–speech sound correspondences. The normal readers outperformed the dyslexic readers for accuracy and speed on a letter–speech sound matching task, as well as on a word-reading task containing familiar words written in the artificial orthography. Importantly, the new artificial script-related measures were related to phonological awareness and rapid automatized naming and made a unique contribution in predicting individual differences in reading and spelling ability. Our results are consistent with the view that a fundamental letter–speech sound learning deficit is a key factor in dyslexia.

Keywords

dyslexia, letter–speech sound learning, dynamic testing, artificial orthography, rapid automatized naming, phonological awareness

Developmental dyslexia, henceforth *dyslexia*, is a disorder that is characterized by disfluent and inaccurate reading that cannot be attributed to low intellectual ability, poor education, or sensory disabilities (Lyon, Shaywitz, & Shaywitz, 2003). Prevalence estimates range from 3% to 10%, depending on the language and the precise criteria used for its assessment (Snowling, 2013). Dyslexia is generally considered a language-based disorder that stems from a deficit in the phonological processing system (Dehaene, 2009; Peterson & Pennington, 2015). It still remains to be elucidated exactly how this phonological deficit leads to reading difficulties, but a prevailing view is that poor phonological awareness (PA) results in reading problems because it hinders the formation of proper letter–speech sound mappings, which is the foundation of reading alphabetic languages (e.g., Peterson & Pennington, 2012; Snowling, 2013).

Research has focused primarily on identifying and understanding the specific phonological shortcomings of dyslexic readers. Surprisingly, the formation of letter–speech sound mappings has long received little attention from an empirical point of view, but during the past few years, this topic has been the focus of growing interest (Hahn, Foxe, & Molholm, 2014; Jones, Kuipers, & Thierry, 2016; Peterson & Pennington, 2015; van Atteveldt & Ansari, 2014). In the current study, we extend this research by examining letter–speech sound learning within an artificial script, focusing on its potential to differentiate between dyslexic readers and normal readers, its contribution to individual differences in reading and spelling skills, and its relation to the phonological shortcomings typically found in dyslexia.

Recent studies, including studies with a cross-linguistic design, substantiate that dyslexic readers typically experience difficulties within two broad phonology-related

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domains—namely, PA and rapid automatized naming (RAN; Boets et al., 2010; Landerl et al., 2013; Ramus & Ahissar, 2012). The former refers to the ability to identify and manipulate speech sounds and is usually assessed by tasks in which speech sounds have to be segmented, blended, replaced, or deleted. An extensive body of research demonstrates that poor PA is one of the strongest correlates associated with reading and spelling disabilities (for a review, see Melby-Lervåg, Lyster, & Hulme, 2012). The latter, RAN, involves naming a series of familiar visually presented items, such as alphanumeric items, colors, or objects, as quickly as possible (Denckla & Rudel, 1976). Poor achievement on RAN tasks is one of the strongest predictors of dyslexia (for a review, see Norton & Wolf, 2012). Findings indicate that 60% to 75% of individuals with a reading disability also exhibit a RAN deficit and that this deficit is present before reading instruction commences (Norton & Wolf, 2012). The double-deficit hypothesis (Wolf & Bowers, 1999) further claims that PA and RAN contribute separately to reading ability and that co-occurrence of these deficits results in the most severely impaired reading skills.

Evidence for disrupted letter–speech sound learning in dyslexia mainly comes from brain potential and neuroimaging research demonstrating that in dyslexia the activity of brain areas involved in the cross-modal integration of letter–speech sound pairs is reduced in response to letter–speech sound associations (Blomert, 2011; Žarić et al., 2014). Behavioral evidence is scarce for deficits of letter–speech sound learning in dyslexia. A few studies have reported that children with dyslexia have difficulties mastering letter–speech sound correspondences (Blomert & Vaessen 2009; Fox, 1994; Siegel & Faux, 1989; Snowling, 1980), but the actual process of learning these mappings was not directly addressed.

In a previous study (Aravena, Snellings, Tijms, & van der Molen, 2013), we examined letter–speech sound learning within an artificial orthography. The script was artificial in the sense that unfamiliar letters (Hebrew) were used to transcribe participants' native language (Dutch). This enabled us to compare the initial steps of dyslexic and non-dyslexic readers in learning a novel script without concerns about possible differences in previous exposure to experimental stimuli. Children were asked to learn eight basic letter–speech sound correspondences within this artificial orthography. After the training, letter knowledge and word-reading ability in the unfamiliar script were assessed. The findings indicated that the basic knowledge of these new correspondences was learned equally well by the children with dyslexia and the normal readers. Importantly, however, normal readers outperformed children with dyslexia when speech sounds had to be matched to their corresponding letters under time pressure. Under these time-restrained conditions, children with dyslexia were much more prone to errors than their controls. The results also demonstrated that normal readers read the artificial script considerably faster than the children with dyslexia. Collectively, these findings indicated that the process of learning letter–speech sound correspondences is impaired in dyslexia.

Current Study

The aims of the current study were twofold. First, the results from our previous study encouraged us to refine the training, optimizing it for further study and making it suitable for diagnostic assessment of dyslexia. We were specifically interested in the potential of this training to predict individual differences in reading and spelling skill and to differentiate between dyslexic readers and normal readers. Second, we wanted to fit the results obtained with this training into the common framework of dyslexia by examining how letter-speech learning relates to PA and RAN and by comparing their contributions to predicting individual differences in reading and spelling ability.

With respect to the first aim, we developed a computerized task that directly measured accuracy and speed of identification of the learned letter–speech sound correspondences. The inclusion of a speed measure is of interest because the extent of audiovisual integration of letter–speech sound correspondences in the brain is primarily reflected in the time course of the neural activation of the concerning units, as well as in the associated response latencies of identification on a behavioral level (Blomert, 2011). We thus created a more sensitive tool that allows for further differentiation even when accuracy performance reaches ceiling levels. Moreover, the learning phase was reduced to 20 min. In our previous study (Aravena et al., 2013), training length was 60 min, but a closer inspection of the data revealed that difficulties in letter–speech sound leaning manifest themselves already halfway through the training. A pilot study indicated that training of only 20 min provided sufficient exposure to all of the stimuli. Such a short duration also makes the training suitable for clinical application.

Besides the benefit of using an artificial script, which allowed for controlling for differences in prior exposure, another important feature of this training is that it is devoted to learning rather than to the level of skill already obtained. An instrument that captures learning in action can be used to identify factors that interfere with the learning of letter–speech sound correspondences. Moreover, this kind of process-oriented testing is potentially capable of predicting future reading gains in dyslexia intervention (Gustafson, Svensson, & Fälth, 2014).

With respect to the second aim, we capitalized on the available data from the diagnostic assessment and compared the scores from the artificial orthography-related tasks with those from PA and RAN tasks with the group of dyslexic children. The fact that the training is orthographically unrelated to standard PA and RAN measures offers a unique opportunity to study the relation between letter–speech sound learning and these traditional measures on a fundamental level, without concerns about reciprocity between literacy and phonological skills. The results thus may shed light on the nature of PA and RAN and how they are related to reading and spelling skills.

Method

Participants

Our sample consisted of 72 children (42 boys and 30 girls) diagnosed with dyslexia and 46 children (22 boys and 24 girls) with average or above-average reading and spelling skills. The age range spans from 7.33 to 11.08 years. All participants were primary education pupils and native speakers of Dutch.

The children diagnosed with dyslexia were recruited from the IWAL Institute, a nationwide center for dyslexia in the Netherlands. Selection of the dyslexic group followed standard criteria for severe dyslexia in the Dutch health care system (Blomert, 2006). Children were selected for the study if they met all three inclusion criteria: (1) Either word-reading speed was ≥1.5 *SD* below average, or word-reading speed was at least 1 *SD* below average with a spelling skill of ≥1.5 *SD* below average; (2) performance on at least two of six administered phonology-related tasks was at least 1.5 *SD* below average; and (3) the child had shown a poor response to intervention provided at school.

The nonimpaired readers were selected from the same sample of schools as the dyslexic readers, to control for socioeconomic status, demography, and level and amount of education. Allocation to the control group was based on the school record. We selected normal-achieving children within general education. Children were selected only when their reading and spelling grades were >25th percentile.

Participant characteristics are shown in Table 1. There were no significant baseline differences between the two groups with respect to age ($p > .05$). We did find a significant baseline difference, however, on the intelligence measure. The dyslexic readers obtained scores close to the general population mean, while the nonimpaired readers obtained scores slightly above this mean. This difference may be an artifact of the aforementioned selection criteria for the nonimpaired readers. To avoid potential confound, we performed additional analyses after matching the two groups on their scores on a nonverbal reasoning task and an expressive vocabulary task. These analyses indicated that group differences in intelligence did not change the pattern of findings.

Exclusion criteria for both groups were uncorrected sensory disabilities, broad neurological deficits, insufficient education, and attention-deficit/hyperactivity disorder. Because we incorporated Hebrew graphemes in our assessment, previous experience with Hebrew script was also an exclusionary criterion. Informed consent was obtained from the parents of each child, and the study was approved by the ethical committee of the university.

Table 1. Participant Characteristics.

	Mean (*SD*)	
Characteristic	Dyslexic group[a]	Control group[b]
Age	9.26 (1.07)	9.37 (0.74)
IQ	5.52 (1.24)	6.38 (1.21)

[a]*n* = 72. [b]*n* = 46.

Training

On the basis of the training that we used in our previous study (Aravena et al., 2013), we developed 20 min of letter–speech sound training consisting of a computer game in which the child had to match speech sounds to their corresponding orthographic representations. Correct associations led to success in the game, while incorrect associations jeopardized a positive outcome. Fast playing was reinforced by progressive time restrictions and by providing bonuses for fast playing. Specifically, children operated a cannon at the bottom of the screen, moving it horizontally. The upper part of the screen was composed of columns of balloons containing single graphemes. Children were required to act on speech sounds that were presented repeatedly in the game. The response consisted of releasing bullets from the cannon and associating them with their corresponding graphemes. When children managed to clear a field of balloons, a new field was presented. As the amount of distractor graphemes increased during the game, fields became gradually more complex. Figure 1 depicts some screenshots from the game.

The goal of the training was to learn a set of letter–speech sound correspondences from an artificial orthography. At the start of the game, the child was presented with a standardized instruction that was integrated in the software. This instruction clarified the specifics of the game but did not reveal the underlying learning objective. After the instruction, children received a short practice trial to become familiar with the setup and the controls of the game. During the training session, children were wearing headphones.

The artificial orthography consisted of eight Hebrew graphemes, which were randomly matched to Dutch phonemes, thereby providing eight basic nonexisting letter–speech sound pairs. The script represents three vowels and five consonants. Combinations of phonemes producing strong coarticulation effects were avoided. Table 2 displays

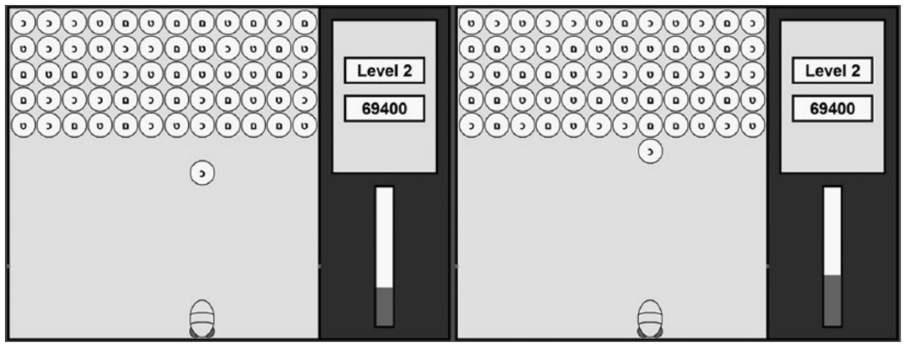

Figure 1. Screenshots from the game.

Table 2. Letter–Speech Sound Correspondences Within the Artificial Orthography.

Item	Correspondence							
Letter	ט	כ	ם	ף	פ	צ	ך	ש
Speech sound[a]	[u]	[ε]	[α]	[k]	[r]	[l]	[t]	[n]

[a]International Phonetic Alphabet.

Table 3. Training-Related Tasks.

	Mean (*SD*)	
Task	Dyslexic group[a]	Control group[b]
Letter–speech sound identification		
Accuracy	50.08 (6.30)	53.65 (1.90)
Speed	1,577.14 (385.37)	1,362.30 (298.41)
No. of words read per second	0.0497 (0.0507)	0.0732 (0.0601)

[a]n = 72. [b]n = 46.

an overview of the letter–speech sound correspondences. The directionality of the script was left to right.

Measures

Letter–speech sound identification task within the artificial orthography. In this task, a phoneme was presented over headphones while two graphemes from the artificial orthography were simultaneously displayed at the screen. One of these graphemes corresponded with the presented phoneme, while the other acted as a distractor. By striking the corresponding button, the child had to decide as fast as possible which grapheme belonged to the presented phoneme. The task consisted of 56 items. Responses, including latencies, were recorded automatically by the software. Accuracy score was defined as the number of correct responses. The speed score was represented by the median of the response latencies of the correct responses.

Reading task within the artificial orthography. We administered a time-limited test (3MAST; Aravena et al., 2013) consisting of a list of 22 high-frequency Dutch words written within the artificial orthography. The words were presented in lowercase Arial typeface, font size 24, and arranged in two columns of equal length. The child had to read (column-wise) as many words as possible within 3 min. The score was determined by the number of words read correctly per second.

Word reading. We used a time-limited task from the *3DM*, a computerized test battery (Blomert & Vaessen, 2009), for assessing word-reading skills in Dutch. This word-reading task included three levels comprising high-frequency words, low-frequency words, and pseudowords. Each level contained 75 words, displayed on five sheets with 15 items each. The difficulty of each level increased systematically from monosyllabic words without consonant clusters to three- or four-syllable words with consonant clusters in the fifth sheet. The child was instructed to accurately read as many words as possible within a time limit of 30 s per level. Both accuracy (percentage of correctly read words) and speed (number of words read correctly) were measured (test-retest: r = .73 and r = .95, respectively).

Spelling recognition. Spelling recognition in Dutch was assessed with a computerized task from the *3DM* (Blomert & Vaessen, 2009). In this task, a word was presented over headphones while it was visible on the screen. In the visually presented word, a letter or letter combination was missing. By striking a key, the child had to decide as fast as possible which of four different letters or letter combinations represented the missing part. Accuracy and response speed were both measured (internal consistency: r = .80 for accuracy and r = .94 for speed).

Spelling to dictation. Spelling to dictation was assessed with the *IWAL Word Dictation Task* (Braams, 1989). This task contained 40 familiar Dutch monosyllabic words, representative of the various spelling problems in Dutch. Scoring was based on the number of spelling errors (test-retest: $r = .89$).

Phonological awareness. We assessed PA with a phoneme deletion task from the *3DM* (Blomert & Vaessen, 2009). In this task, the child had to delete consonants from aurally presented pseudowords as fast as possible. The score was determined by the percentage of correct responses (internal consistency: $r = .85$).

Rapid automatized naming. We assessed RAN of letters and digits with a task from the *3DM* (Blomert & Vaessen, 2009). The child had to name aloud items presented on the computer screen as fast and accurate as possible. Within both domains, sheets containing 15 items each were presented two times. The score per subtask was determined by taking the mean response speed of the two sheets (split-half reliability: $r = .80$ for letters and $r = .83$ for digits). In the current study, we used a composite measure of alphanumeric RAN consisting of the scores from letters and digits.

Intelligence measure. General intelligence was assessed by the subtest Analogies from the SON-R (*Snijders-Oomen Non-Verbal Intelligence Test*; Laros & Tellegen, 1991), a nonverbal reasoning-by-analogy task in which the child had to extract a principle and to apply it to a new situation (test-retest: $r = .79$), and the Vocabulary subtest from the WISC-III (*Wechsler Intelligence Scale for Children–Third Edition*, Dutch version; Kort et al., 2005), a measure of expressive vocabulary requiring the child to describe the meaning of words of increasing complexity (test-retest: $r = .90$). The score was determined by averaging the standardized C-scores ($M = 5$, $SD = 2$) of both tests.

Baseline response speed. We assessed baseline response speed using a task from the *3DM* (Blomert & Vaessen, 2009). In this task, four horizontally arranged squares were presented on the computer screen. Whenever a figure appeared in one of the squares, the child had to respond to it, as fast and accurately as possible, by striking the corresponding key. Mean reaction time was computed across 20 items (internal consistency: $r = .93$).

Procedure

The session, which had a duration of approximately 1 hr, took place on a one-to-one basis and consisted of four steps. First, we provided the 20-min letter–speech sound training. After the training, we administered the letter–speech sound identification task and the reading task within the artificial orthography consecutively. These two tasks took approximately 10 min. In the remaining 30 min, we assessed nonverbal reasoning and expressive vocabulary. The nonimpaired readers attended their session at school and the dyslexic readers, at the nearest branch of the dyslexia institute. All sessions took place in a silent room. For both the training and the letter–speech sound identification task, we used a 15.6-in. laptop computer (ThinkPad Edge, Model 0319; Lenovo, Morrisville, NC) in full-screen mode. We derived the scores concerning reading and spelling, PA, RAN, and baseline response speed from the standard diagnostic assessment of the dyslexic children. The training session and subsequent assessment took place on the same day as this diagnostic assessment.

Results

Differentiating Dyslexic and Normal Readers

To examine whether the brief training would differentiate between dyslexic and normal readers, we compared both groups on the various artificial orthography-related measures. First, we conducted an independent t test to determine whether dyslexic readers and controls differed with regard to the identification of letter–speech sound correspondences in the artificial orthography. The mean scores and standard deviations thus obtained are shown in Table 3. The results indicate that, on average, controls were more accurate than the dyslexic readers on the identification task, $t(89, 773) = -4.496$, $p = .001$, with a medium to large effect size ($r = .43$). Moreover, the controls responded faster than the dyslexic readers on the same test, $t(111, 648) = 3.397$, $p = .001$, with a medium effect size ($r = .30$).

A second analysis focused on the ability to read the novel script following training. Table 3 displays the mean scores and standard deviations. The results from the independent t test show that the controls read significantly more words per second than the dyslexic children, $t(115) = -2.279$, $p = .013$, with a modest effect size ($r = .21$).

Predicting Group Membership

To gain more insight into the extent to which the measures from the brief training are able to correctly predict group membership (dyslexic readers vs. typical readers), we conducted logistic regression analysis and receiver operator characteristic (ROC) curve analysis (Swets, 1988). The results of these analyses indicate that both the accuracy measure, $\text{Exp}(B) = 1.24$, $p = .007$, and speed measure, $\text{Exp}(B) = 1.00$, $p = .034$, from the identification task made a significant contribution to predicting group membership. Classification based on these two measures was accurate at 68.6% (see Table 4). As indicated by the ROC analysis, area under the curve = .74, $p < .001$, the diagnostic

Table 4. Logistic Regression Analysis Predicting Presence of Dyslexia With Cutoff Value p = .05.

	Predicted		Prediction rate, %
	Dyslexic group	Control group	
Observed, *n*			
Dyslexic	55	17	76.4
Control	20	26	56.5
Prediction rate, %	73.3	60.5	

accuracy of the identification task can be classified as fair (Youngstrom, 2014).

With an overall prediction rate of 62.4%, the number of words read per second also made a significant contribution to predicting group membership, Exp(B) = 2,332.352, p = .03. The ROC analysis, area under the curve = .65, p = .007, indicated low to moderate diagnostic accuracy (Youngstrom, 2014), making it less suitable for clinical application. Accordingly, adding this measure to the aforementioned logistic regression model did not significantly improve its ability to correctly predict group membership.

These findings indicate that after only 20 min of training, the controls outperformed the dyslexic readers in identifying the newly learned letter–speech sound correspondences. Although accuracy was high overall, the dyslexic readers made substantially more errors (11%) than the normal readers (4%). Importantly, these differences in mastery between the groups, expressed in accuracy as well as in speed, also resulted in significant differences in the number of words read per second.

Correlation Analysis

To determine the relation among the measures that were used to tap letter–speech sound learning within the artificial orthography, the traditional phonological measures, and reading and spelling skills, we computed Pearson semipartial correlations, from which the concomitant effect of age was removed. Note, that, as discussed in the introduction, these analyses were conducted only with the group of dyslexic readers. All correlations are presented in Table 5. The results indicate that the reading task within the artificial orthography correlated significantly with PA and RAN. Furthermore, the speed measure of the identification task correlated significantly with RAN. This correlation was still significant after controlling for baseline response speed, r = .396, p = .001.

We observed that the reading accuracy measure was moderately correlated with the number of words read per second within the artificial orthography but not with other measures. Reading speed showed a pronounced correlation with RAN and the number of words read per second within the artificial orthography and a moderate correlation with the speed measure of the identification task. For the computerized spelling recognition task, accuracy was found to be moderately correlated to PA, accuracy on the identification task, and the number of words read per second within the artificial orthography. Speed of spelling recognition showed a strong correlation with RAN and speed on the identification task and a moderate correlation with the number of words read per second within the artificial orthography. Furthermore, we found the number of errors on word dictation to be strongly correlated with PA and the number of words read per second within the artificial orthography and to be moderately correlated to accuracy on the letter–speech sound identification task. All significant correlations were in the expected direction.

Predicting Individual Differences in Reading and Spelling Skill

We explored the contribution of each of the five variables in predicting individual differences in reading and spelling skills using relative importance weight (RIW) analyses. RIW analysis is an extension of multiple regression that allows for more accurate partitioning of variance and that is particularly suitable for estimating the relative importance of predictor variables that are correlated with one another (Johnson, 2000; Tonidandel & LeBreton, 2011). We adopted this additional procedure, as we were primarily interested in the relative importance of our new predictor variables versus the well-established traditional predictors and less in their absolute contribution to the coefficient of determination. This was all the more important because the age range of our sample was relatively wide, while the variance of the dependent variables and predictor variables was limited because the analyses referred only to the sample of children diagnosed with dyslexia. Moreover, given the intercorrelations of our predictors, beta coefficients might not be the best suited to index relative importance (Kraha, Turner, Nimon, Zientek, & Henson, 2012; O'Neill, McLarnon, Schneider, & Gardner, 2014). RIW improves the interpretation of results of multiple regression within this context by transforming predictor variables into their maximally related orthogonal counterparts and using these transformed variables to predict the criterion (Johnson, 2000). Tables 6 and 7 display the outcomes of the regression analyses on which the RIW analyses of the current study are based.

In each analysis, age was entered on the first step, while the five predictor variables—PA, alphanumeric RAN, identification of letter–speech sound correspondences (accuracy and speed), and the number of words read per second within the artificial orthography—were entered as the second step. The results indicate that, in all analyses, age accounted for a substantial amount of variance. As mentioned, this result

Table 5. Correlation Matrix (Semipartial).

	1	2	3	4	5	6	7	8	9
1: L-SS identification accuracy (artificial)	1								
2: L-SS identification speed (artificial)	–.043	1							
3: Words per second (artificial)	.413**	–.377**	1						
4: Phonological awareness	.086	–.150	.293**	1					
5: Rapid naming alphanumeric	–.085	.414**	–.237*	.082	1				
6: Word reading accuracy	.015	.075	.237*	.191	.004	1			
7: Word reading speed	.147	–.214*	.392**	–.071	–.488**	.416**	1		
8: Spelling recognition accuracy	.312*	–.058	.198*	.250*	–.069	.245*	.297*	1	
9: Spelling recognition speed	.057	.334**	–.223*	–.052	.327**	–.128	–.414**	.031	1
10: Spelling to dictation	–.221*	.098	–.407**	–.439**	.007	–.382**	–.402**	–.491**	.147

Note. $N = 71$. L-SS = letter–speech sound.
*$p < .05$. **$p < .01$.

Table 6. Regression Model Predicting Reading Measures.

		Reading accuracy		Reading speed	
Step	Measure	R^2	ΔR^2	R^2	ΔR^2
1	Age	.19	.19**	.39	.39**
2	PA, RAN, L-SSa, L-SSs, WPS	.29	.10	.59	.20**

Note. PA = phonological awareness; RAN = rapid automatized naming; L-SSa = letter–speech sound identification accuracy; L-SSs = letter–speech sound identification speed; WPS = words per second read in the artificial orthography.
**$p < .01$.

Table 7. Regression Models Predicting Spelling Measures.

		Spelling accuracy		Spelling speed		Spelling to dictation	
Step	Measure	R^2	ΔR^2	R^2	ΔR^2	R^2	ΔR^2
1	Age	.36	.36**	.39	.39**	.33	.33**
2	PA, RAN, L-SSa, L-SSs, WPS	.47	.11*	.59	.20**	.52	.19**

Note. PA = phonological awareness; RAN = rapid automatized naming; L-SSa = letter–speech sound identification accuracy; L-SSs = letter–speech sound identification speed; WPS = words per second read in the artificial orthography.
*$p < .05$. **$p < .01$.

was expected due to the rather wide age range of our sample and the limited room for variance of the predictor variables within the sample of children diagnosed with dyslexia. More important, our results indicated that the predictors of interest made additional contributions in accounting for group differences in reading and spelling skills. The findings from the RIW analyses, which are presented in Figure 2, shed light on the relative contribution of each predictor variable. Note that this figure shows a set of weights that represent each predictor's relative importance to the prediction of the criterion in the context of the total variance accounted for by the set of predictors. To provide insight into the extent to which the RIW analyses had an impact on the relative contribution of the predictors, the results from multiple regression analyses are presented in the appendix to provide a frame of reference. The overall picture of these multiple regression analyses is consistent with the RIW analyses, showing a significant and unique contribution of the artificial orthography-related measures to predicting individual differences in reading and spelling skills.

When it comes to predicting reading accuracy, the number of words read per second within the artificial orthography contributed more than half (53%) to the remainder of the coefficient of determination after age was accounted for (ΔR^2 of Step 2). Most of the remaining variance was claimed by PA (24%) and speed on the letter–speech sound identification task (18%). With regard to reading speed, the most important contribution to the ΔR^2 of Step 2 came from RAN (54%), followed by the number of words read per second within the artificial orthography (34%). For the spelling recognition tasks, the accuracy measure was best predicted by accuracy on the letter–speech sound identification tasks (52,6%), followed by PA (35%). We obtained a different pattern of results when decomposing the remainder of the R^2 of the speed measure of the spelling recognition task. Here, RAN (39%) and speed on the letter–speech sound identification task (36%) were responsible for the largest contribution. The number of words read per second within the artificial orthography claimed a modest part of the remainder of the R^2 for both accuracy (9%) and speed (17%) of the spelling recognition task. In predicting the spelling-to-dictation task, PA contributed most to the ΔR^2 of Step 2 (52%), followed by the number of words read per second within the artificial orthography (37%).

To sum up, the results demonstrate that 20-min letter–speech sound training within an artificial orthography

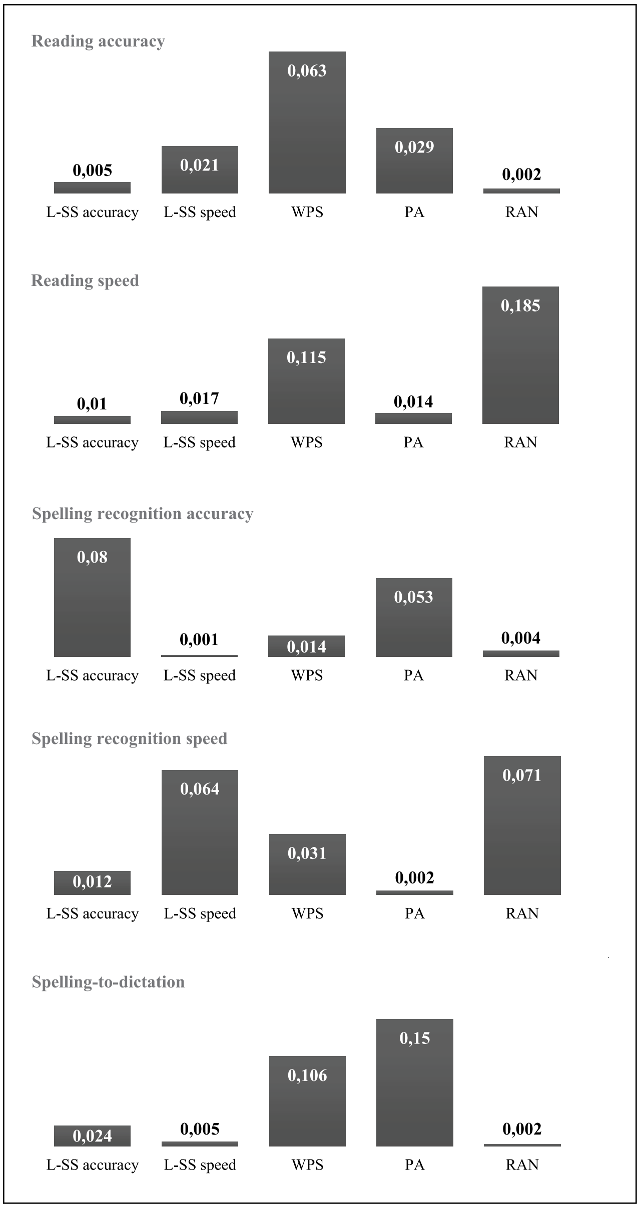

Figure 2. Relative importance weights analyses.

differentiates between dyslexic and normal readers. The effect of this training is related to PA and RAN and makes a substantial and unique contribution in predicting individual differences in reading and spelling ability when compared with these traditional predictors.

Discussion

In the current study, we examined letter–speech sound learning within an artificial script and focused on its potential to differentiate between dyslexic readers and normal readers, its contribution to variance in reading and spelling skills, and its relation to PA and RAN. We employed relatively short training (only 20 min) aimed at the learning of eight basic letter–speech sound correspondences within an artificial orthography, followed by a short assessment of mastery of these correspondences and word-reading ability in this unfamiliar script.

Our results indicate that the short training is successful in differentiating dyslexic readers from normal readers in their ability to learn letter–speech sound correspondences. The normal readers outperformed the dyslexic readers on accuracy and speed on a letter–speech sound identification task and on a word-reading task containing familiar words written in the artificial orthography. These results fit well with our earlier finding that dyslexic readers are fundamentally hampered in their ability to learn letter-speech correspondences and that the manifestation of this binding deficit can be evoked at any time by presenting them with a novel script (Aravena et al., 2013), giving further support for the notion that a letter–speech sound binding deficit is a key factor in dyslexia (Blomert, 2011; Hahn et al., 2014; Jones et al., 2016; van Atteveldt & Ansari, 2014).

To assess how letter–speech sound learning within an artificial orthography relates to traditional phonological measures, we examined PA and RAN within the group of dyslexic children and conducted correlational analyses. In line with studies indicating that RAN taps nonphonological cognitive components important to reading (Norton & Wolf, 2012), we did not find a significant correlation between the scores on the phoneme deletion tasks and the alphanumeric RAN task. However, we did observe RAN to be strongly related to the speed measure of the letter–speech sound identification task within the artificial orthography, which is interesting given the fact that the tasks are orthographically dissimilar. We believe that this finding is important in that it may contribute to the ongoing discussion on the mechanisms that are responsible for the relation between RAN and reading. Possible mediators between RAN and reading that have commonly been put forward in this context are phonological processing, orthographic processing, processing speed, serial processing, and articulation of specific names (Georgiou, Parrila, & Papadopoulos, 2016; Kirby, Georgiou, Martinussen, & Parrila, 2010). Interestingly, none of these factors seem to be a likely candidate for explaining the correlation between RAN and the speed measure of the letter–speech sound identification task within the artificial orthography. The current observation that these measures are orthographically unrelated and that neither is correlated to PA indicates that the relation must not be sought in phonological or orthographical knowledge. Neither does general processing speed seem to be the underlying factor, as controlling for baseline response speed did not affect the correlation between measures. Last, as our letter–speech sound identification task does not appeal to serial processing nor to articulation, it seems that the observed correlation between alphanumeric RAN and speed on the letter–speech sound identification task within the artificial orthography must originate from some other factor—one that also may drive the relationship between RAN and reading. A plausible interpretation would be that speed of letter–speech sound identification provides a potential index of the ability to instrumentally use newly learned letter–speech sound correspondences in reading. Poorly integrated letter–speech sound mappings therefore lead to slow and laborious naming and, following this, poor reading as well. On this account, it is the extent to which letter–speech sound correspondences are automatized that mediates RAN and reading proficiency. This interpretation is consistent with the view put forward by Wolf and Bowers (1999), who suggested that disturbed naming speed may result in reading failure because of impeded amalgamation of connections between phonemes and orthographic patterns.

We also obtained a correlation between RAN and the number of words read per second in the artificial script. This is not a surprise, given the fact that this task also capitalizes on efficient letter–speech sound learning. It was unexpected, however, that the number of words read per second also correlated with PA, while the two measures from the letter–speech sound identification task were unrelated to PA. A possible explanation for this finding is that, although the tasks are orthographically unrelated, they both strongly appeal to a decoding skill. From this perspective, the number of words read per second in the artificial script is correlated with RAN because both tasks depend on mastery of letter–speech sound correspondences and with PA because both tasks require decoding skills.

Considering the correlations between the traditional phonological measures and the new artificial orthography-related measures, on one hand, and the various reading and spelling measures on the other, we see a familiar pattern of results in which PA seems to be more related to accuracy measures of reading and spelling, while RAN is more related to speed measures of reading and spelling. The findings from our artificial orthography-based measures reflect this accuracy-speed division, with accuracy on the identification task predicting reading and spelling accuracy and with speed on the identification task predicting reading and spelling speed. Intriguingly, the number of words read per second within the artificial orthography correlated significantly with all reading and spelling measures within our study and thus does not seem to mesh with the accuracy-speed division. As the number of words read per second within the artificial orthography is correlated with all other measures, it seems that this task shares components with phonology-related skills as well as with reading and spelling, irrespective of whether accuracy or speed is the focus of attention.

Note that the results from the correlational analysis do not coincide with the findings from the *t* test. Based on the high correlation of the number of words read per second with other relevant measures, one would expect it to be the most effective measure to differentiate between the two groups. However, the *t* test shows that dyslexic and normal readers seem to differ only moderately on the reading task within the artificial orthography. This unexpected finding might indicate that the artificial reading task is related more strongly to reading among typical readers than the measures from the identification task. Accordingly, the identification task differentiates better between the two groups. This interpretation must remain speculative given the differential amounts of data collected from our dyslectic versus typically reading participants.

In view of the potential value of the three artificial orthography-related measures for clinical practice, we applied relative weight analyses to examine the relative contribution of these new measures vis-à-vis the traditional combination of PA and RAN. The findings indicated that the new predictors made meaningful and partly independent contributions to explaining individual differences in reading and spelling skills. A combination of conventional testing and these new measures thus constitutes a stronger predictor of individual differences in reading and spelling skills than conventional testing alone, which stresses the potential benefit of the current learning procedure for the clinical assessment of dyslexia.

The finding that the number of words read per second within the artificial orthography predicts reading and spelling, as well as accuracy and speed, raises questions about the nature of this skill. What exactly does it embody? We believe that this skill probably requires the ability to instrumentally use newly learned letter–speech sound correspondences. It is this ability that determines whether someone succeeds in applying the new mappings within a cognitively demanding task, such as reading. By this, we do not imply that our task provides a tool to directly assess the integration of letter–speech sound correspondences. Of course, such a process needs much more time to be accomplished. But we do believe that it reveals a fundamental underlying problem responsible for the hampered integration of letter–speech sound correspondences. Moreover, in addition to the mastery of letter–speech sound correspondences, fast reading within the artificial orthography requires a decoding skill within a context that does not support fast orthographic pattern recognition, which explains its relation with PA and makes it a strong predictor of individual differences in reading and spelling skills within the domain of accuracy and speed.

Naturally, there are other possible explanations why the number of words read per second within the artificial orthography predicts different reading and spelling measures. A decoding skill seems to be an important factor related to this task, and besides a letter–speech sound learning deficit, other difficulties may lead to decoding problems. Therefore, we cannot rule out other mediating factors, such as difficulties storing speech sounds in working memory (e.g., Wang, Allen, Lee, & Hsieh, 2015).

An important theoretical question concerns the relationship between deficient letter–speech sound learning and the assumed deficit in the phonological processing system. We did not obtain evidence for the view that poor PA results in reading problems because it hinders the establishment of proper letter–speech sound mappings. Letter–speech sound identification within the artificial orthography was not found to be correlated to PA. Moreover, the measures related to the artificial orthography contributed uniquely in accounting for the variance in reading and spelling skills. Given this pattern of results, it seems unlikely that disrupted letter–speech sound learning could be simply explained as a result of poor PA or any other phonological factors. It rather seems that disrupted letter–speech sound learning is at least a partly independent factor underlying dyslexia. This conclusion is in line with findings reported by Blomert and Willems (2010) and McNorgan, Randazzo-Wagner, and Booth (2013).

The current procedure is particularly suitable for cross-linguistic comparison of individuals with dyslexia, as it is not restricted to a specific language. This is of considerable interest because the complexity of the particular orthography that an individual has to master has been identified as a central environmental factor associated with dyslexia (Landerl et al., 2013; Seymour, Aro, & Erskine, 2003). Some adjustments to the set of phonemes might be necessary, though, because results across languages can be compared only when phonemes are shared or nonexistent in each of them. Taking this into account, the current training could be used as a universal measure for assessing the strength of letter–speech sound learning. A similar approach could be adopted for diagnosing dyslexia in a second language. Standard reading and spelling measures, as well as phonology-related measures, usually fall short because they cannot discard the confounding influence of less language proficiency in the second language. In a recent study, Elbro, Daugaard, and Gellert (2012) demonstrated that dynamic assessment of acquiring decoding abilities in an artificial script provides a useful way of circumventing this confounding influence in the context of assessing dyslexia.

Suggestions for Future Research

An interesting avenue for future research would be to explore letter–speech sound learning in individuals with severe reading and spelling difficulties who do not show a phonological deficit. The fact that not all children with persistent phonological deficits develop reading disabilities and that some children show severe reading disabilities despite normal phonological abilities has led to the view that although phonological deficits are standard in dyslexia, multiple factors, including nonphonological factors, interact in a complex way to cause reading impairment (Peterson & Pennington, 2012). An example of a nonphonological factor that has been proposed as an independent cause of reading impairment is poor visual attention (e.g., Bosse, Tainturier, & Valdois, 2007). According to this point of view, reading acquisition is impaired because the quantity of visual information that can be processed at a glance is reduced. It would be of interest to investigate whether children with poor visual attention span but intact phonological abilities also perform poor when adopting the procedure developed in the current study.

Conclusion

Our findings show that brief training for efficiently learning new letter–speech sound correspondences predicts individual differences in reading and spelling ability and contributes moderately but significantly to predicting group membership. It seems that pooling the strengths of conventional testing and the current training procedure could improve the assessment of dyslexia. Particularly, the number of words read per second within the artificial orthography was valuable in this context, as it seems to predict variance within a range of reading and spelling skills, within both the speed and accuracy domains. Importantly, the training refers to learning artificial letter–speech sound correspondences. This implies that there are no a priori differences in exposure to the stimuli at the start of the assessment. In this respect, the training would provide a relatively "pure" assessment as compared with traditional instruments, in the sense that typical reciprocity between reading development and phonological development is circumvented. Traditional tests can be used to determine if letter–speech sound correspondences are weak, but they do not tell whether this should be attributed to a predisposition, to reading problems, or to differences in exposure. In contrast, the current learning procedure allows for the detection of a fundamental learning deficit for letter–speech sound associations. Finally, we stress that the current training procedure is dynamic. Where traditional diagnostic instruments focus on learning that took place prior to the assessment, the current training is carried out as part of the assessment. This kind of process-oriented testing would be a welcome complement to the diagnostician's toolbox in the clinical practice of dyslexia. Diagnostic assessment should also focus on learning, as dyslexia is classified in terms of a learning disability. Process-oriented diagnostic tools are potentially capable of predicting future reading gains in dyslexia intervention (Gustafson et al., 2014), which is interesting given the current paucity in our knowledge of factors that predict responsiveness to dyslexia intervention (Frijters, 2011; Hoeft et al., 2011; Tijms, 2011).

Appendix

Multiple Regression Analyses Predicting Reading and Spelling Measures.

	Reading accuracy		Reading speed		Spelling accuracy		Spelling speed		Spelling to dictation	
	R^2	ΔR^2	R^2	ΔR^2	R^2	ΔR^2	R^2	ΔR^2	R^2	ΔR^2
1 Age	.19	.19**	.39	.39**	.36	.36**	.27	.27**	.33	.33**
2 PA	.21	.03	.39	.00	.44	.08**	.27	.00	.46	.14**
3 RAN	.21	.00	.53	.14**	.44	.01	.35	.08**	.47	.00
4 L-SSa	.21	.00	.54	.00	.47	.03*	.36	.01	.48	.02
5 L-SSs	.23	.01	.54	.00	.47	.00	.39	.03*	.48	.00
6 WPS	.29	.06*	.59	.05**	.47	.00	.40	.01	.52	.04*
2 WPS	.23	.05*	.48	.09**	.38	.02	.31	.04*	.44	.11**
3 PA	.25	.01	.50	.02	.44	.06**	.31	.00	.52	.08**
4 RAN	.25	.00	.59	.09**	.44	.00	.37	.06**	.52	.00
5 L-SSa	.25	.01	.59	.00	.47	.03*	.38	.02	.52	.00
6 L-SSs	.29	.03*	.59	.00	.47	.00	.40	.02	.52	.00
2 L-SSs	.19	.01	.42	.03*	.37	.01	.35	.08**	.33	.01
3 WPS	.26	.07**	.48	.06**	.38	.02	.36	.01	.44	.11**
4 PA	.28	.01	.50	.02	.44	.06**	.36	.00	.52	.08**
5 RAN	.28	.00	.58	.09**	.44	.00	.39	.03*	.52	.00
6 L-SSa	.29	.01	.59	.00	.47	.03*	.40	.01	.52	.00
2 L-SSa	.19	.00	.39	.01	.40	.04*	.27	.00	.36	.03*
3 L-SSs	.19	.01	.42	.03*	.41	.00	.36	.08**	.36	.01
4 WPS	.27	.08**	.48	.06**	.41	.00	.37	.02	.44	.08**
5 PA	.29	.01	.50	.02	.47	.06**	.37	.00	.52	.08**
6 RAN	.29	.00	.59	.09**	.47	.00	.40	.03*	.52	.00
2 RAN	.19	.00	.53	.15**	.36	.00	.35	.08**	.33	.00
3 L-SSa	.19	.00	.54	.00	.40	.04*	.35	.01	.36	.03*
4 L-SSs	.19	.01	.54	.00	.41	.00	.39	.04*	.37	.01
5 WPS	.27	.08**	.58	.05**	.41	.00	.40	.01	.45	.08**
6 PA	.29	.01	.59	.01	.47	.06**	.40	.00	.52	.07**

Note. PA = phonological awareness; RAN = rapid automatized naming; L-SSa = letter–speech sound identification accuracy; L-SSs = letter–speech sound identification speed; WPS = words per second read in the artificial orthography.
*$p < .05$. **$p < .01$.

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