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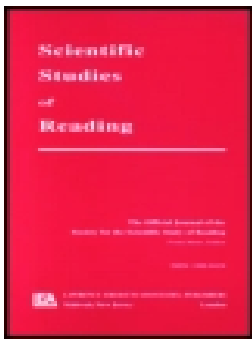
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Statistical Learning of Speech Sounds in Dyslexic and Typical Reading Children

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ABSTRACT

Statistical learning has been proposed to underlie the developmental transition during infancy from allophonic to phonemic speech sound perception. Based on this, it can be hypothesized that in dyslexic individuals, core phonemic representation deficits arise from reduced sensitivity to the statistical distribution of sounds. This study aims to investigate (a) whether statistical learning contributes to the construction of phonemic representations in typical readers, and (b) whether deficits in statistical learning underlie dyslexia. Fifty-eight children performed an identification task of a non-native phonetic contrast, before and after exposure to the sounds of the continuum. Our results suggest that the statistical distribution of the presented sounds implicitly enhanced the formation of phonemic representations and that dyslexic readers make less use of the statistical cues embedded in oral language, resulting in less distinct phonemic categories and thus a higher risk for failing to establish robust connections between these and written language.

Introduction

To make consistent grapheme–phoneme couplings when learning to read in alphabetic orthographies, a child should have well-specified phonemic representations that are robust against acoustic variations induced by different speakers, dialects, or contexts. According to the predominant cognitive explanation of developmental dyslexia, the severe and persistent reading impairments that define dyslexic readers (DR) arise from an underlying phonological deficit (for evidence for a possible causal link between phonological processing and reading, see the longitudinal studies of Boets, Smedt, & Cleuren, 2010; Law, Vandermosten, Ghesquière, & Wouters, 2017; Muter, Hulme, Snowling, & Stevenson, 2004; but see also Castles & Coltheart, 2004, for a critical review). Phonological problems are expressed in a variety of tasks (such as phonological awareness, verbal short-term memory, and rapid verbal retrieval tasks), with poorly specified phonemic representations being considered the common source (Vellutino, Fletcher, Snowling, & Scanlon, 2004). Although evidence for such a representational deficit in dyslexia remains surprisingly scarce, especially in adults (Boets et al., 2013; Ramus & Szenkovits, 2008), indirect support is found in dyslexic children's poor performance in categorizing phonemes (see Table 1 in Vandermosten et al., 2011, for an overview) and in priming (Boada & Pennington, 2006) and event-related potential studies (Bruder et al., 2011; Hornickel & Kraus, 2013).

Because dyslexia is a developmental *learning* disability, it is relevant to examine not only the outcome of deficient development (i.e., less distinctive phonological representations) but also the process of how these representations are constructed. From a developmental perspective, two main mechanisms seem to play a crucial role. First, infants need to be able to perceive the subtle acoustic

cues (often occurring within only tens of milliseconds) that distinguish different speech sounds, hence requiring good auditory abilities (Hornickel & Kraus, 2013; Vandermosten et al., 2010). Second, between the ages of 6 and 12 months, infants must learn to perceptually assimilate sounds belonging to the same phonetic entity even though they hear them as being distinct; this is referred to as *categorical perception of phonemes* (Kuhl, 2004). Statistical learning has been proposed to be the main mechanism responsible for this developmental change from allophonic (i.e., perceiving different exemplars of specific speech sounds as being different) to phonemic (i.e., perceiving only speech sounds that belong to different phoneme categories as being distinct) listening (McMurray, Aslin, & Toscano, 2009). The language input we experience is very diverse, but it contains recurring patterns. Statistical learning refers to the ability to implicitly learn to detect and extract the regularities that are present in our language (Perruchet & Pacton, 2006). A pioneering research study by Saffran and colleagues (1996), which was later replicated and extended by many others (for reviews, see Arciuli & von Koss Torkildsen, 2012; Saffran, 2003), demonstrated the importance of sensitivity to statistical regularities in syllable sequences for the segmentation of a continuous stream of speech into words. Furthermore, it has been shown that sensitivity to these statistical cues has a positive effect on later language development (Estes, Evans, Alibali, & Saffran, 2007; Evans, Saffran, & Robe-Torres, 2009; Newman, Ratner, Jusczyk, Jusczyk, & Dow, 2006; Tsao, Liu, & Kuhl, 2004). These language studies all focused on a specific subtype of statistical learning, that is, conditional statistical learning, in which serial order regularities are implicitly detected and used to define word boundaries. However, the role of distributional statistical learning (i.e., learning to use the frequency distribution of individual exemplars to form prototypes; Perruchet & Pacton, 2006; Romberg & Saffran, 2013) has been studied much less frequently despite its potential relevance for forming phonemic representations. In one study, it has been demonstrated that infants use the distribution of sounds of their native language to define the phonemic structure of that language (Maye, Weiss, & Aslin, 2008). More specifically, if the end points of a /d/ – /t/ continuum are presented more frequently than the other sounds to the infants, then two separate sound categories are formed, whereas if stimuli from the middle of the continuum (i.e., at the phoneme boundary) are more frequently presented, then only one, wider phonemic category is formed. Sensitivity to the distributional properties of speech sounds has also been demonstrated in adults, where categories were acquired after exposure to bimodally distributed non-native sounds (Hayes-Harb, 2007). This statistical learning mechanism helps to explain why adult listeners hear the /r/ and /l/ sounds as being either distinct (English speakers) or identical (Japanese speakers). Despite the fact that in both languages highly variable sounds occur, in English the sounds at the endpoints of the /r/ – /l/ continuum are the most frequent, and distributional frequencies are low at the phoneme boundary, whereas in Japanese there is a unimodal frequency distribution, with sounds at the boundary occurring most frequently (Kuhl, 2004). Of interest, also in the visual domain it has been shown that distributional cues play an important role in allowing infants to learn to identify and categorize faces (Altvater-Mackensen, Jessen, & Grossmann, 2017).

In the dyslexia literature, opposing views exist regarding which of the two building blocks, that is, auditory processing or (statistical) learning, hampers the construction of phoneme representations. Auditory processing has frequently been investigated in dyslexia, and empirical evidence, often—though not always—has confirmed the presence of an auditory deficit, especially when stimuli contain acoustic changes over time (Hämäläinen, Salminen, & Leppänen, 2012). The observed auditory impairments can hinder phoneme perception (Talcott et al., 2002; Vandermosten et al., 2010, 2011) but can also affect other aspects of speech processing such as syllable identification and the processing of prosody (Goswami, 2015; Halliday, Tuomainen, & Rosen, 2017; Law et al., 2017; Poelmans et al., 2011). Moreover, auditory deficits can only partially explain the variability seen in dyslexics' phonological and reading performance (Law et al., 2017); hence, deficient statistical learning might also contribute. As indicated by Pennington's (2006) multiple deficit model, dyslexia is likely to be the result of multiple contributive cognitive factors that interact with one another, with different relative weightings of each factor across individuals. Evidence for a deficit in statistical learning in dyslexia comes from experiments having shown that sensitivity to conditional regularities of visual symbols correlated with reading skills

(Arciuli & Simpson, 2012) and was often lower in children and adults with dyslexia (Pavlidou & Williams, 2014; Vicari et al., 2005; Vicari, Marotta, Menghini, Molinari, & Petrosini, 2003; but see Rüsseler, Ye, Gerth, Szycik, & Münte, 2017), especially in conditions of high statistical complexity (Du & Kelly, 2013). In the auditory domain, it has also been shown that conditional regularities in the sequence of syllables, phonemes, and nonspeech sounds are difficult to detect for poor readers (Bonte, Poelmans, & Blomert, 2007; Gabay, Thiessen, & Holt, 2015). Although there is currently insufficient evidence to draw firm conclusions (for a detailed review, see Schmalz, Altoè, & Mulatti, 2017), there are at least indications that statistical learning of conditional regularities is hindered in dyslexia. Yet it is currently not known whether sensitivity to distributional cues, which is crucial for the building up of phoneme representations, is also hampered in this disorder. Hence, although the core deficit in dyslexia is often assumed to be at the phonetic level in terms of the processing of, access to, and representation of speech sounds, it has not yet been investigated whether the use of statistical distributional cues, which play a direct role in the formation of phoneme categories, is also hampered in poor readers.

The objective of the present study was twofold. First, we aimed to extend previous findings from infants (Maye, Werker, & Gerken, 2002) and adults (Hayes-Harb, 2007) by investigating whether statistical learning, and more specifically distributional learning, plays a role in the formation of phoneme categories in school-age children (Grade 3). Second, we aimed to compare statistical learning between typical reading children and children with dyslexia to determine whether differences in such learning might underlie a core phonological-processing deficit in dyslexia. For the first aim, we compared phonetic identification performance in two groups of typically reading children, before and after exposure to a non-native Hindi dental-retroflex contrast that is not phonemically distinctive in their native language (i.e., Dutch). The learning of non-native contrasts can be used to mimic the formation of native speech sound categories that takes place during early development in infants. By manipulating the distributional patterns of the sounds, we can assess the extent to which this process is dependent on statistical regularities. We assessed this by exposing half of the typical readers (TR) to a unimodal distribution of items from the dental-retroflex contrast (i.e., by presenting sounds from the middle of the stimulus continuum more frequently) and by exposing the remaining participants to a bimodal distribution of items (i.e., more frequent exposure to the two endpoints of the continuum). We predicted that if statistical learning contributes to speech sound acquisition, after exposure the children from the bimodal group would be successful in perceiving the non-native phoneme contrast (i.e., that they would hear them as two separate categories), whereas the children from the unimodal group would not hear the difference between the dental and retroflex sounds. To address the second aim of assessing potential statistical learning deficits in dyslexia, we compared TR and poor readers on their sensitivity to these distributional properties of speech. To this end, we tested whether typical reading children benefit more from exposure to a bimodal frequency distribution of the non-native speech sounds than do children with dyslexia.

Method

Participants

Fifty-eight Dutch-speaking children attending third grade of primary school participated in this study. Of these, 39 were TR and 19 were DR. The TR were randomly assigned to two groups, with one group listening to a bimodal distribution of the non-native dental-retroflex continuum during the exposure session (TR–bimodal, $N = 20$) and the other group to a unimodal distribution (TR–unimodal, $N = 19$; see Figure 1). TR children had no diagnosis of dyslexia and reported no history of reading problems. We wanted to ensure that children in the TR group perform above the 10th percentile on a standardized Dutch word reading test (Brus & Voeten, 1973), which we assessed in Grade 3. Three of the TR (one from the TR–bimodal group and two from the TR–unimodal group) scored below the 10th percentile on the word reading test despite no reported reading problems. In addition, although none of the subjects had been exposed to Indian languages, three of the TR did not have Dutch as their mother tongue but learned
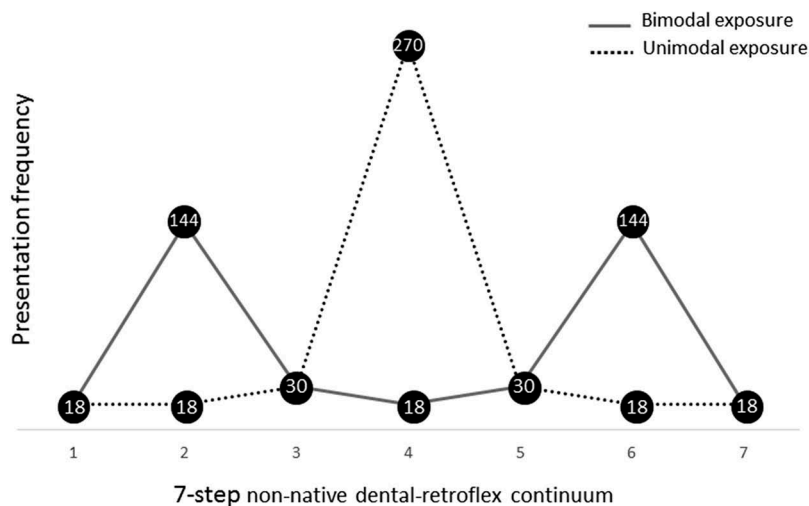
Figure 1. The frequency distribution of each stimulus of the dental-retroflex continuum during the exposure session. *Note.* The speech sound continuum is shown on the x-axis, with Stimulus 1 corresponding to the dental phoneme followed by the vowel /a/ and Stimulus 7 to the retroflex counterpart. Numbers in the solid circles represent the number of times that specific stimuli were presented during the respective unimodal (dotted lines) and bimodal (solid gray lines) protocols. Stimuli 1, 3, 5, and 7 were presented equally frequently across the two exposure protocols.

it as a second language at school (all from the TR–unimodal group; no overlap with three poor reading TR). We included these poor reading and non-native Dutch TR subjects in the experiment but also reran the analyses excluding them, and this resulted in the same pattern of results (see Supplementary Information). For the second part of our study, 19 native Dutch-speaking children with dyslexia were tested on the bimodal condition only (DR–bimodal), and their performance was compared to that of the TR–bimodal group. To be classified as dyslexic, severity and persistence criteria had to be fulfilled, in line with diagnostic criteria for dyslexia in Flanders and the Netherlands (Gersons-Wolfensberger & Ruijssenaars, 1997). First, the severity of the reading problem was defined by scores below the 10th percentile on a standardized Grade 3–level word reading test (Brus & Voeten, 1973). Second, persistence of the reading problem was operationalized by a formal dyslexia diagnosis (DR–bimodal: $N = 17$) and/or by repetitive poor reading performance on the standardized school tests of the pupil monitoring system (i.e., below the 15th percentile) at the end of Grades 1 and 2 (DR–bimodal: $N = 16$). Table 1 shows that the three groups (TR–bimodal, TR–unimodal, DR–bimodal) were matched for nonverbal IQ (as assessed by the Wechsler Intelligence Scale for Children bloc patterns), age, and gender. As expected from the

Table 1. Subject Characteristics and Reading Measures in Typical Readers Exposed to a Unimodal Speech Sound Distribution (TR–Unimodal), Typical Readers Exposed to a Bimodal Distribution (TR–Bimodal), and Dyslexic Readers Exposed to a Bimodal Distribution (DR–Bimodal)

	TR–Unimodal	TR–Bimodal	DR–Bimodal	Test Statistics
	M (SD)	M (SD)	M (SD)	
Subject characteristics				
N	19	20	19	
Sex (boy/girl)	11/9	11/9	12/7	$\chi^2(2) = 0.47, p = .789$
Age (months)	107.00 (4.38)	108.00 (4.82)	105.37 (4.87)	$F(2) = 1.55, p = .222$
WISC (Bloc patterns)[a]	10.37 (2.77)	10.60 (2.95)	11.42 (2.93)	$F(2) = 0.70, p = .501$
Reading measures Grade 3				
Word reading[a]	10.05 (2.99)a	9.50 (3.00)a	2.78 (1.87)b	$F(2) = 43.53, p < .001$
Pseudoword reading[a]	10.42 (2.78)a	10.15 (2.23)a	6.68 (2.16)b	$F(2) = 14.40, p < .001$

Note. Groups that differ significantly ($p = .001$) have a different subscript letter. WISC = Wechsler Intelligence Scale for Children.
[a]Standardized scores with $M = 10$, $SD = 3$.

reading group classification, both TR groups (TR–unimodal and TR–bimodal) differed significantly from the DR–bimodal group on word and pseudoword reading ($p < .001$) but did not differ from each other on these skills ($p > .798$).

Statistical learning experiment

Non-native stimuli

We used the same seven-step synthetic non-native dental-retroflex place-of-articulation continuum as used in Golestani, Paus, and Zatorre (2002) and Golestani and Zatorre (2009). The first end point of the continuum consisted of a dental-voiced unaspirated stop consonant /d/ followed by the vowel /a/, and the last endpoint (Stimulus 7) consisted of the retroflex counterpart. The middle stimuli were interpolations of the dental and retroflex endpoint prototypes, resulting in a continuum that had equal acoustic differences between each of the adjacent stimuli of the continuum. This retroflex consonant is rare across languages and does not exist as a Dutch phoneme, allowing us to ensure that our Dutch-speaking participants, of whom none had been exposed to Indian languages, have not had phonemic exposure to this sound. Further, previous studies have confirmed that native speakers of languages that don't employ this contrast as a phonemic distinction (e.g., French: Golestani, Molko, Dehaene, LeBihan, & Pallier, 2007; Ramus & Szenkovits, 2008; e.g., English: Golestani et al., 2002) cannot distinguish this sound from its native counterpart (e.g., dental in French and alveolar in English). It has also been shown that infants not exposed to this contrast phonetically in their day-to-day linguistic environment no longer hear this contrast by 10 months of age (Tees & Werker, 1984). Although it is difficult for people who do not speak Indian languages to hear this contrast, with training, improvements do occur even though there are large individual differences in the amount of improvement across individuals (Golestani & Zatorre, 2009; Werker & Tees, 1983, 2002). Thus, by choosing this contrast we ensured that participants could not hear this contrast at baseline, allowing room for improvement after exposure during the statistical learning experiment. The synthesis of the retroflex-dental continuum was based on parameters reported in Stevens and Blumstein (1975). These four-formant stimuli were constructed using the signal processing language software MITSYN (Henke, 1990) and the Klatt model synthesizer. The continuum was created by manipulating the transition of formant 3 (from 3080 to 2414 Hz, using equal step sizes of 111 Hz between adjacent stimuli) and the center frequency of the burst (from 4500 to 3189 Hz, using equal step sizes of 217 Hz). Each stimulus lasted 220 ms, including a burst that lasted 5 ms and a 40-ms-long formant transition.

Exposure session to non-native stimuli

To test whether exposure to a bimodal distribution of speech sounds induces learning of a non-native contrast in typical reading children, we presented half of the TR children with a bimodally distributed seven-step non-native dental-retroflex continuum, and the other half with a unimodal distribution (subjects were randomly assigned to the groups). In Figure 1 it is demonstrated that the stimulus distribution for bimodal exposure was 18× Stimulus 1, 144× Stimulus 2, 30× Stimulus 3, 18× Stimulus 4, 30× Stimulus 5, 144× Stimulus 6, 18× Stimulus 7. For unimodal exposure, the stimulus distribution was: 18× Stimulus 1, 18× Stimulus 2, 30× Stimulus 3, 270× Stimulus 4, 30× Stimulus 5, 18× Stimulus 6, 18× Stimulus 7. To keep the attention of the children focused on the speech sounds, catch trials were presented 21 times throughout the exposure session. On these catch trials, the child had to press a response button within 2 s of when he or she heard a naturally spoken /dada/ (this natural sound could be easily discriminated from those of the synthetic dental-retroflex continuum). Exposure to the non-native continuum and the catch trials lasted together approximately 8–10 min, similarly to previous experiments on statistical learning of phonemes in adolescence (Hayes-Harb, 2007), and longer than the 2.5 min of exposure that has been shown to work in infants (Maye et al., 2002). Based on previous studies (Golestani et al., 2007, 2002; Golestani & Zatorre, 2009), we expected that before exposure, identification performance would be at chance levels.

Non-native identification task

An identification task was administered to test how consistently children attributed Hindi sounds to the same phonetic category despite small acoustic differences. To assess potential improvements in phonemic perception after the exposure session, we administered the identification task twice, directly before and after the exposure session. Familiarization and brief practice were given before the actual test trials, but only test trials were used to assess performance on the identification task. Familiarization and practice trials were included to teach children the associated labels and to get them acquainted with the test procedure. First, during 20 familiarization trials, participants listened to each of the two end point stimuli 10 times (presented in alternation), and the associated label (i.e., correct answer) was provided visually. Next, during eight practice trials, each of the two end point stimuli was presented four times in random order. For each practice trial, participants had to indicate which of the two sounds they had heard, after which feedback regarding accuracy was provided. Next came the test trials, where in each block, each of the seven stimuli from the continuum was presented twice, in random order. Again, on each trial, participants had to indicate which sound they had heard, but now no feedback was given. Two more 14-trial test blocks were administered, with two short practice blocks of four trials (each end point presented twice, with feedback) in between the testing blocks. These additional practice blocks were administered to ensure that for subjects having learned the sound-label associations, their labels would not be accidentally reversed over the course of testing, as has previously been observed to happen in adults (Golestani & Zatorre, 2009). In total, the identification task included 42 trials, with each of the seven stimuli being presented six times. The task was administered using a child-friendly approach, in the context of a story about two little monsters whose languages the children needed to learn. The dental sound corresponded to the language of a purple monster, and the retroflex sound corresponded to that of an orange monster.

Native sound categorization

Native stimuli

We used the same 10-step native phonetic continuum as in Vandermosten and colleagues (2010, 2011). The continuum was created in PRAAT, starting from a naturalistic spoken /ba/and extrapolated in 10 equal steps to a /da/. The manipulated part of the signal was a 100-ms interval at the beginning of the sound, and the F2 onset ranged from 830 to 1906 Hz, whereas the steady-state part of the vowel was kept at 1100 Hz. Each item of the resulting 10-step continuum had a total length of 350 ms.

Native identification task

A bada continuum was presented by means of a two-alternative forced-choice identification task embedded within a computer game (Boets et al., 2011). The child was instructed to point to the picture of a *bak* or a *dak* (i.e., the Dutch words for 'basket' and 'roof') that corresponded to the heard sound. The time to respond was unlimited, and no feedback was given. The task was preceded by a pretest, presenting each of the two end point stimuli five times.

Data analysis

For the Hindi identification data as well as the /bada/ identification data, we fitted the slope of the identification curve at the category boundary of each individual, as this provides information about how consistently sounds are categorized (Maassen, Groenen, Cru, Assman-Hulsmans, & Gabreëls, 2001). Individual identification data were submitted to a cumulative Gaussian function using a generalized linear model in the statistical software R (R Foundation for Statistical Computing). The slope was calculated based on the proportion of times that participants provided the label corresponding to the endpoint stimulus (Stimulus 7 for the Hindi contrast and Stimulus 10 for the bada construct), for each stimulus. If participants can differentiate the sounds, the slope of the identification curve is positive because the proportion of Label

7 and Label 10 responses for the Hindi and bada continuum, respectively, will be high for stimuli close or equal to these end points and low for stimuli close or equal to Stimulus 1. For the Hindi sounds, fittings were not possible for seven subjects in the pre-exposure test (2 DR–bimodal, 1 TR–bimodal, 4 TR–unimodal) and in six subjects in the postexposure test (3 DR–bimodal, 1 TR–bimodal, 2 TR–unimodal) because the proportion of Stimulus 7 responses was for each stimulus step below 50%. This implies a performance at chance; hence, for these subjects slopes were set at zero (i.e., flat curve). Data of the Hindi-identification task, which was administered before and after the exposure to either a bimodal or unimodal distribution, were analyzed using mixed-model analyses. In the mixed-model analyses, group was included as a between-subjects variable and measure point as a within-subjects variable, and with the slope of the identification functions of the Hindi continuum as the dependent variable. Significant interactions were further explored using post hoc testing. Data of the bada-identification task and accuracy on the catch trials during the exposure session were analyses using a two-sample t test with group as an independent variable and slope of the identification curve as dependent variable.

Results

TR–unimodal versus TR–bimodal

To examine whether statistical learning contributes to the construction of phonemic representations in TR, we analyzed the data using mixed models, with exposure group (TR–bimodal vs. TR–unimodal) as a between-subjects variable and measure point (pre- vs. postidentification test) as a within-subjects variable, and with the slope of the identification functions as the dependent variable (see Panels a and b of Figure 2). We observed a significant main effect of measure point, $F(1, 37) = 4.17$, $p = .048$, and of interest, the interaction between exposure group by measure point was also close to significance, $F(1, 37) = 3.32$, $p = .076$. Given our a priori predictions of a posttraining improvement in performance in the TR–bimodal group specifically, we further investigated this interaction using planned comparisons. This revealed that the unimodal group did not improve in categorizing the non-native sounds, $t(37) = 0.15$, $p = .879$, whereas the bimodal group did display a significantly steeper slope at the post relative to the preexposure test, $t(37) = 2.77$, $p = .009$. This was further confirmed by no significant difference between the uni- and bimodal group in the slope of the preexposure test, $t(37) = 0.05$, $p = .962$, whereas there was a group difference in the slope of the postexposure test, $t(37) = 2.63$, $p = .013$.

The same pattern of results was obtained when the three subjects with poor reading scores were excluded from the analyses, with again a significant improvement after exposure in the TR–bimodal group, $t(34) = 2.37$, $p = .024$, and a significant difference between the TR–unimodal and TR–bimodal group in the postexposure test, $t(34) = 2.46$, $p = .019$.
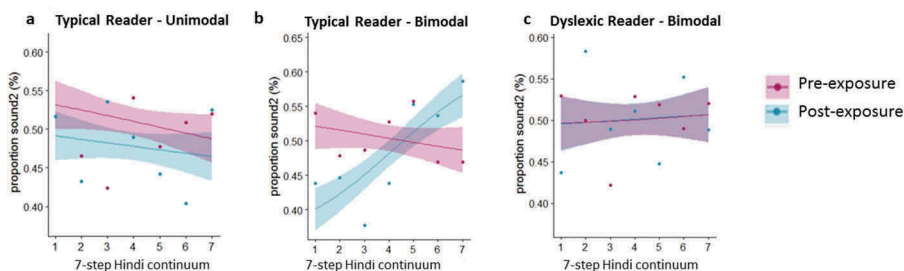
Figure 2. Psychometric fittings of the non-native identification data in typical reading children exposed to a unimodal distribution of Hindi-sounds (Typical Reader–Unimodal), typical reading children exposed to bimodal distribution (Typical Reader–Bimodal), and dyslexic reading children exposed to a bimodal distribution (Dyslexic Reader–Bimodal). *Note.* The curve represents the average of the individually fitted slopes of the different subjects, and the background shaded regions (in red for the preexposure condition and in blue for the postexposure condition) represent the average error bars of the fit to the data across subject.

TR–bimodal versus DR–bimodal

To examine whether deficits in statistical learning are present in children with dyslexia, we compared the performance of 20 typical reading children (TR–bimodal, same children as the bimodal group of Step 1) to that of 19 poor reading children (DR–bimodal), both having been exposed to a bimodal distribution. We analyzed the data using mixed models, again with slope of the identification tests as the dependent variable, with reading group (TR–bimodal vs. DR–bimodal) as a between-subjects variable and with measure point (pre- vs. postidentification test) as a within-subjects variable (see Panel b of Figure 2). Results revealed strong trends for the main effect of measure point, $F(1, 36) = 4.04$, $p = .052$, as well as for the Reading Group × Measure Point interaction, $F(1, 36) = 4.05$, $p = .052$. In contrast to the TR–bimodal group, which exhibited a significantly steeper slope in the postrelative to the preexposure test (see earlier), planned comparisons, performed based on the a priori prediction that there would be greater improvement in the TR–bimodal compared to the DR–bimodal group, revealed no improvement in the DR–bimodal group, $t(36) = -0.00$, $p = .999$. This is also in line with a nonsignificant difference between the poor reading and typical reading groups in the slope of the preexposure test, $t(36) = 0.57$, $p = .575$, and a concurrent group difference in the slope of the postexposure test, $t(36) = -2.27$, $p = .029$. Finally, to examine whether task demand and attentional effects were driving the observed group differences in learning, we investigated group differences in the slope of the bada identification task that had similar task demands as the Hindi identification task, and we investigated the accuracy for the catch trials as an index of sustained attention throughout exposure. If the TR–bimodal and DR–bimodal groups also display significant group differences for these variables, attentional and task demand aspects might play a role in the observed group differences in learning. Although there was a significant group difference in the slope of the bada identifcation task between DR–bimodal and all TR (both TR–unimodal and TR–bimodal), $t(53.8) = -2.15$, $p = .036$, the DR–bimodal and TR–modal group did not differ significantly from each other, $t(31.7) = -1.55$, $p = .132$. Concerning the attentional processes, no significant group differences were observed between DR and TR, $t(22.54) = 1.60$, $p = .124$, or between DR and the subgroup of TR, which had been exposed to the bimodal distribution, $t(26.10) = 1.62$, $p = .117$.

Discussion

In this study, we showed that typical reading Grade 3 children could learn to hear phoneme differences in non-native sounds by implicitly relying on information contained within the frequency distribution of these sounds. In addition, we showed that dyslexic reading children, in contrast to typical reading children, did not benefit from exposure to a bimodal distribution: This distributional information did not allow them to implicitly learn to hear differences between non-native speech sounds.

Focusing on auditory processing deficits as an explanation for dyslexic's phonological problems, especially for explaining problems at the phoneme level, has a long tradition in dyslexia research (Tallal, 1980), though not without controversy (Ramus, 2003). However, although the ability to hear subtle auditory differences is a necessary condition for phoneme identification, it is not sufficient. Our perceptual system still needs to learn which auditory differences are relevant (i.e., differences between phoneme categories) and which are not (i.e., within-category, allophonic differences; Goldstone & Hendrickson, 2010). Ambiguous phonetic variants that could correspond to either of two phoneme categories are produced less often than variants that more clearly belong to one phoneme category (Werker et al., 2007), and infants use this frequency information to form phonemic categories (Maye et al., 2002). Our study extends this latter finding by showing that school-age children remain sensitive to the distributional frequency of speech sounds, and that they use it to learn to hear phoneme differences. This was supported by the finding of a significantly steeper phoneme identification slope in children who listened to a bimodal distribution than in children who listened to a unimodal speech sound distribution. This improvement occurred already after a short exposure time of around 8 min, whereas previous studies having trained this very dental-retroflex continuum generally required 15–20 min of training, albeit in adults (Golestani et al., 2007; Golestani et al., 2002; Golestani & Zatorre, 2009). This might suggest that tapping into statistical regularities is a very

efficient way of learning new categories. Also, the implicit nature of our learning paradigm (i.e., no active response required during listening to the sounds) might result in enhanced learning compared to when explicit feedback is provided (Vlahou, Protopapas, & Seitz, 2012), at least on condition that attention is payed to the stimuli (Turk-Brown, Jungé, & Scholl, 2005). Future research could compare implicit exposure and explicit training paradigms in order to determine whether implicit learning using bimodal distributions is the most optimal design for phoneme learning in children, as is suggested to be the case in adults (Vlahou et al., 2012). Note, however, that although learning after bimodal exposure was observed in TR at the group level, almost half of the group was still at chance levels and the other half did not reach its full potential of phonemic categorization. Future studies should therefore investigate whether increasing the exposure time in young children—if it does not come at the cost of poorer attention and cooperation—could induce phonemic learning in all subjects while preserving large interindividual variability in the degree of learning. It would also be interesting to investigate whether a unimodal distribution in which two neighboring middle stimuli are frequently presented would induce more learning than the current unimodal distribution in which the possibility of performing direct comparisons between neighboring stimuli is minimized, as only one middle stimulus is frequently presented.

With regard to dyslexia, our results indicate that failure in the formation of phonemic representations might be explained not only by auditory impairments (Goswami, 2011; Poelmans et al., 2011; Vandermosten et al., 2010) but also by reduced statistical learning skills. This was supported by our additional analyses suggesting that reduced learning in DR is due not to paying less attention during the exposure or to task demands inherent to the identification task but to an compromised statistical learning mechanism. Nevertheless, caution is warrant given our small sample size, so replications are needed to draw firmer conclusions. There is a renewed interest in investigating the learning component of dyslexia for explaining its etiology (Krishnan, Watkins, & Bishop, 2016), including research on statistical learning (Schmalz et al., 2017). The mixed results in existing studies might be explained by a lack of a clear link between the statistical learning abilities tested and reading skills. Most of these studies have focused on conditional statistical learning, and it has been proposed that this is an important mechanism for reading by ways of supporting the detection of orthographic regularities in written language (i.e., the pronunciation of a letter is often dependent on the surrounding letters) and of graphotactic patterns (i.e., rules about which letter combinations are allowed; Arciuli & von Koss Torkildsen, 2012). Yet this type of statistical learning does not feed directly into the formation of phoneme categories and its associated phonological problems in dyslexia. Information on distributional statistical learning of phonemes might be more directly relevant to the reading encoding problems that DR experience. This is supported by Spencer and colleagues (2015), who found that in typically developing children (from kindergarten to second grade) distributional learning predicted phonological processing to a greater extent than conditional learning. Statistical learning appears not to be one unified ability but rather a componential ability covering different subtypes (distributional and conditional) and different types of input (e.g., linguistic vs. nonlinguistic, auditory vs. visual), each of which can be independently impaired (Frost, Armstrong, Siegelman, & Christiansen, 2015; Siegelman & Frost, 2015). Future studies can thus explore different types of statistical learning with different modalities of input within the same subjects and look for relationships with reading ability for each of them.

To conclude, according to statistical learning principles, separate sound categories can be formed via implicit learning of the frequency distribution of sounds (Hayes-Harb, 2007; Maye et al., 2002), and this is indeed what we observed in typical reading 9-year-olds. Speech sounds that are unimodally distributed along a continuum incorporate acoustic variation that is uninformative for distinguishing phonemes, whereas bimodal distributions signal the linguistic importance of a contrast. However, age-matched children with dyslexia seem not to be able to benefit from this distributional information. Early in development this might hamper the formation of well-specified and nonoverlapping phonemic representations, and due to the necessity of learning to map speech sounds to symbols in reading acquisition, this can result in a failure to read. However, longitudinal studies, preferably starting in infancy when phonemic categories are learned, are needed to understand the putative causal link between statistical learning of speech sounds and reading ability.

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