

Speech Perception in Children with Reading Disabilities: Phonetic Processing is the Problem

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Abstract

Purpose: Reading disability (RD) is a key obstacle in the development of literacy, and studies show that 15-20% of grade-school students have an RD. The current study examines one potential source of RD in young children (8-12 years old): inadequate open set, non-categorical speech processing abilities, which may be related to early language development.

Method: We present data from two tasks: **(1)** A 3-interval forced choice procedure called the *Syllable Confusion Oddball (SCO)* task, which examines the listener's ability to identify different syllables (CV/VC) from a string of three such syllables, spoken by three different talkers, selected from a database of 18 adult mixed-gender talkers. **(2)** A single CV/VC presentation task with a verbal response, denoted the *Nonsense Syllable Confusion Matrix (NSCM)* task, where the listener labels individual utterances of CV and VC sounds. Ten children having well-documented RDs, normal hearing, and normal language function completed the tasks, and their performance was compared to that of six reading control (RC) children with no RD. The consonants and vowels each had 4.2 bits of entropy (19 vowels and 19 consonants), providing a sufficient range of responses to investigate perceptual confusions and differences in error rates.

Results: For the SCO task, the proportion of errors was significantly higher for the RD listeners compared with the RC listeners; the RD listeners had, on average, three to five times as many errors as the RC listeners. These errors were also highly idiosyncratic, with differences between individual subjects in the errors they made as a function of phone type (consonant vs. vowel) and syllable position (initial vs. final). Results from the NSCM task revealed individual differences in the confusion patterns for these errors.

Conclusions: Three main conclusions can be drawn from the results:**(1)** RD children have a significant speech perception problem in identifying open set syllables, despite normal pure-tone hearing and language processing abilities. **(2)** For the NSCM task, the errors were somewhat reduced, indicating that the single-interval task was easier than the three-interval task. **(3)** These results are at odds with previous work which shows no indication of phoneme identification impairment in RD children. However, previous studies were significantly limited in the number of trials, the number of speech sounds that were tested, and the type and extent of trials used.

Keywords: reading disability, speech perception, phone encoding

Speech Perception in Children with Reading Disabilities: Phonetic Processing is the Problem

In typically-developing (TD) children, speech perception happens naturally, even effortlessly. The ability to discriminate and identify speech sounds provides the foundation for learning to produce and comprehend spoken language. In contrast, learning to read requires considerable instruction and practice. One of the first steps in learning to read is *decoding*, which involves translating printed words to sounds. Indeed, accurate decoding can be seen as fundamental to the reading process, as suggested by Hanford (2018): “The starting point for reading is sound. A child who can’t decode will never become a reader.”

Decoding is also central to current models of reading, in that it provides the learner with the basic knowledge needed to map letters onto speech sounds and eventually directly to lexical representations (Seidenberg and McClelland, 1989). The decoding process can be contrasted with *encoding*, which involves mapping speech sounds to syllables, letters, or words. Clearly, basic encoding, allowing the listener to accurately recognize speech sounds, must be mastered before decoding can be taught. Thus, before teaching children to read, it is assumed they have normal speech perception (encoding) skills.

Issues with decoding and (possibly) encoding become relevant when we consider that a considerable number of children have difficulty learning to read, and many are diagnosed with having a *reading disability* (RD). Understanding the nature of RDs is critically important, as a lack of literacy skills is associated with a number of negative outcomes. For instance, according to national statistics, based on the 1994 Washington Summit on Learning Disabilities (Ellis and Cramer, 1994; NICHD/NRP, 2000a,b), 50% of inmates cannot read.

Moreover, understanding of the precise source of any RD could impact the success rate of treatment. Given this, and assuming that the encoding process is central to learning to read, one might naturally ask: (1) To what extent is accurate phonetic encoding important for reading, and (2) Can disruptions in phonetic encoding during early childhood lead to RD? For example, middle ear infections are common in early childhood, and these frequently lead to a temporary (less than one year), undetected 50 dB hearing loss (Williams and Jacobs, 2009). This could lead to a substantial disruption in exposure to speech sounds, impacting speech development, and thus contributing to RD.

In the current study, we ask whether reading development depends on the seemingly-easy preschool task of understanding speech (i.e., encoding), and we will show that RD children do not have TD speech perception. We investigate these issues by examining the speech perception abilities of RD children and

TD *reading control* (RC) children. Specifically, we examine how accurately children recognize and classify speech sounds in a quiet environment (i.e., with no added noise) using a large database of natural speech sounds. This provides a measure of the listener's sensitivity to fine phonetic detail in the speech signal, which is necessary for accurate encoding (Allen, 2005; Phatak and Allen, 2007; Toscano and Allen, 2014).

We will first consider previous work on speech perception in RD children, as well as current models of reading that provide the basis for the experiment presented here. Next we present results from two tasks designed to measure listeners' speech perception abilities. Finally, implications for models of reading and approaches for RD interventions are discussed.

Learning to read

The processes of learning to understand spoken language and learning to read can be viewed in terms of three *information channels*: auditory, contextual, and visual (Miller et al., 1951; Bronkhorst et al., 1993; Allen, 2005; Kamhi and Catts, 2012). In order to understand speech, infants must first recognize phones or syllables (i.e., speech sounds via the auditory channel) and then associate speech with words (i.e., meaning via the contextual channel). These processes occur early for spoken language (between 1-18 months; Eimas et al., 1971; Jusczyk, 2000), long before learning to read.

Around 3-4 years, TD children can begin recognizing letters (the visual channel), and by around 5-6 years, they can begin learning to decode letters. Note that, critically, reading must be taught—it is *not* spontaneously acquired—unlike spoken language. Thus, the auditory and contextual channels may be viewed as fundamental to language comprehension, and ultimately to reading ability, in that they provide the foundation for decoding. This view is similar to that offered by connectionist approaches and other models of reading (Gough and Tunmer, 1986; Harm et al., 2003; Hoover and Gough, 1990; Plaut et al., 1996; Seidenberg and McClelland, 1989), which demonstrate that successful reading depends on decoding. These basic models can also explain the effects of word frequency and spelling-sound consistency on reading (Plaut et al., 1996), and they help to explain the effectiveness of RD interventions that focus on learning to decode (Harm et al., 2003). Other work has argued that children learn to read by blending onsets and rimes to recognize single-syllable words in print (e.g., the onset of “c” and the rime “at”, blended to read the word “cat”; Goswami and Bryant, 1990).

Taken as a whole, current models of reading demonstrate that the key factor in children's success

depends on their ability to decode letters. However, this view assumes that the mapping from sounds onto words (i.e., encoding) is already well-established and that children can accurately recognize basic speech sounds (phones). To study when and how speech perception (i.e., the contribution of the auditory channel) impacts reading ability, one must first eliminate contributions from the visual and contextual channels, particularly given that higher-level linguistic information can influence early speech sound encoding in meaningful contexts (Getz and Toscano, in press). Therefore, in the current study we avoid the use of text and meaning in order to specifically test the auditory perception abilities of RD subjects. To achieve this, we use tasks that measure basic phonetic encoding abilities, following approaches used in studying perception of natural speech sounds by Fletcher (1929), Miller et al. (1951) and Miller and Nicely (1955), as summarized in Allen (2005).

To see how disruptions in phonetic encoding may play a role in learning to read, consider the processes involved in speech perception. These were described in Harvey Fletcher's early work on the Articulation Index (AI) model of speech recognition, outlined in Fig. 1. To account for the identification of speech sounds, Fletcher identified a cascade of processing tasks, starting with cochlear filtering, followed by the identification of speech features (events), phones, syllables and eventually, meaningful words (Allen, 1996). Previous work has not suggested that this model is relevant to reading, but we shall argue that Fletcher's model provides key insights into the reading process. In particular, it suggests that accurate phone processing (encoding) must be functional before a child can begin learning to read.

RD interventions

Given the models described above, what determines whether children successfully learn to read or whether they have a RD? One challenge in answering these questions is that the criteria used to define and diagnose reading problems are necessarily complex. For example, dyslexia, a type of RD, specifically refers to difficulties with recognizing words in print (Kamhi and Catts, 2012).¹ However, dyslexia may be characterized on the basis of not only word recognition ability, but also spelling and visual decoding skills. Furthermore, dyslexia is correlated with performance on other aspects of reading, such as vocabulary, grammar, comprehension, and reasoning. Thus, dyslexia involves a broad range of abilities, many of which are interrelated. Despite the complexities involved in defining RD, we would expect that interventions

¹ We use the more general term *reading disability* (RD) to refer to any disruption in reading ability.

focusing on letter decoding would be most successful, given the models of reading described above. Indeed, there is considerable evidence that teaching decoding skills (otherwise known as phonics) specifically improves reading outcomes (NICHD/NRP, 2000a,b).

Other interventions have focused on *phonological awareness*, another key skill for children to master in order to become successful readers. However, this view assumes a skill of explicitly attending to, judging, and manipulating the structure of speech sounds at the syllable level. It typically aims to assess how children recognize speech sounds in a meaningful contexts (i.e., words). There have been at least three decades of studies on phonological awareness (Goswami and Bryant, 1990; Kamhi and Catts, 2012), and research on the topic is ongoing (DeGroot et al., 2015). Interventions based on phonological awareness have been argued to improve reading ability. Bradley and Bryant (1983) presented a study on word training using CVCs with 65 children who had significant reading difficulties, performing at least one standard deviation below the mean in reading level. A subset of the RD group received phonemic awareness training via visual presentations, which caused them to improve greatly in reading compared with the group that did not receive such training. Because the cohort was taken from a group of subjects from a previous test of reading ability on the same words, the experiment was longitudinally controlled. Hence, the experiment provided one of the first demonstrations of a causal relation between phonological awareness and improvement in reading ability. Bradley and Bryant (1978) found a similar relationship between phonological awareness and improvement in reading abilities.

However, as noted above, it is difficult to isolate speech perception problems using tasks that only involve meaningful words, due to context effects (Miller et al., 1951). Thus, a useful strategy is to break the problem into smaller parts, along its natural boundaries, and tackle them one after another, as summarized in Fig. 1 (Allen, 2005, Fig. 1.3, p. 18). This is the approach we take in the current study.

RD and speech perception

Both decoding and phonological awareness interventions assume that the child can accurately encode speech sounds, and both of these skills depend on processes that lie at the very last stage of the speech recognition process. This is illustrated by Fletcher's model (Fig. 1), where phones (i.e., individual speech sounds) are mapped onto syllables, which are woven into meaningful contexts such as words. Thus, the most basic (i.e., earliest) step in perceiving speech is phone recognition (Li and Allen, 2011). As a

result, perception of phone differences may well determine the success of reading and language comprehension. Given this, we aim to specifically investigate low-level phone perception as the first step in the analysis of reading problems. This approach is supported by other reading research as well. For example, Share and Stanovich (1995) note that contextual information plays a less important role than phonological sensitivity in reading comprehension, suggesting a reason to focus on phone perception.

Several earlier studies have investigated the role of speech perception in RD. Many of these studies have used the *categorical perception* paradigm, where speech sounds are varied along specific acoustic-phonetic continua and listeners' identification and discrimination responses are compared (Liberman et al., 1957).² Brandt and Rosen (1980) used this approach to measure perception of speech sounds in 12 RD children and four TD children who served as reading control (RC) subjects. Listeners were tested with synthetic CV syllables varying along a voice onset time (VOT) continuum distinguishing voicing (/b,p/) and formant transition continua distinguishing place of articulation (/b,d,g/), each presented in the context of the vowel /a/. They concluded that there was no significant difference in categorical perception between the RD and RC children.

Other studies have examined RD children's perception of speech sounds for meaningful words. Manis et al. (1997) investigated this with 25 dyslexic (DYS) children (4th-10th grade), whose performance was compared with 25 chronological age (CA) matched children (5th-8th grade) and 24 reading level (RL) matched children (2nd-3rd grade). The spoken words *bath* (/bæθ/) and *path* (/pæθ/) were used as testing materials to measure /b/-/p/ categorization ability of the groups of subjects. In general, the slopes (*b*) of the categorization curves for the DYS group were shallower than those of the CA group but were not different from the RL group. Similarly, Joanisse et al. (2000) looked at phoneme categorization with 61 DYS 3rd graders (7-10 years old), 52 CA matched 3rd graders, and 37 RL matched 1st and 2nd graders (6-8 years old), testing phoneme categorization with the word pairs *dug-tug* and *spy-sky*. They found no overall difference in categorization between the DYS and control groups, but a subset of DYS subjects

² These studies have often used synthetic speech in order to create sounds that vary along specific acoustic dimensions and control for variability between speech sounds (Liberman et al., 1967). We now better understand the nature of this variability and can control for it (Li and Allen, 2011), and more recent work has used natural speech sound continua instead (Toscano and McMurray, 2012; Toscano and Lansing, in press). In the current study, natural speech is chosen over synthetic speech as it provides a rich set of acoustic cues used by the auditory system that are distinct from those found in synthetic speech sounds (Li et al., 2010; Li and Allen, 2011).

showed shallower categorization functions for both speech sound contrasts.

Phone perception research

The studies described above have primarily focused on using the categorical perception paradigm and involve varying stimuli (often synthetic speech sounds) along specific acoustic dimensions. While this provides a high degree of control over the stimuli, it does not capture the large variability present in natural speech. Moreover, these studies have often focused on only a small subset of speech sounds, often examining stop consonants, which may be recognized more accurately than other types of speech sounds. As described below, other work has aimed to measure speech perception in children with RD using larger sets of speech sounds in other types of tasks that may allow us to better measure perception of sub-phonemic (i.e., phone-level) differences in speech.

Hazan and Adlard (1998) measured speech sound discrimination in 13 children with reading delays, 12 reading-age (RA) matched controls, and 12 chronological-age (CA) matched controls. Children were presented with several tasks, including a same-different speech sound discrimination task with stimuli presented in a VCV syllable structure, where the consonant was one of /b,d,g,k,v,ʒ,ʃ, s,f,m,n, ɪ,w,j,l/, all presented in the context of the vowel /a/. There was no overall difference between the groups, but there was an interaction between group and consonant, such that children in the RD group made more errors for stop consonants. A subset of RD children were also found to make more errors overall compared with RC children across different speech sounds.

Messaoud-Galusi et al. (2011) carried out consonant identification and discrimination experiments using several different tasks with 62 DYS and 51 control children, examining perception of the contrast between /b/ and /p/ in quiet and in 20-talker babble noise. As in the studies described above, they found that the DYS subjects showed shallower identification functions than control subjects, but only for speech presented in quiet. In addition, DYS subjects showed poorer within-category phoneme discrimination; evidence of differences in across-category discrimination was mixed and depended on the specific task used. Overall, the authors conclude that there were not consistent speech perception deficits associated with dyslexia. This experiment was a follow-up of a similar study done with adults (Hazan et al., 2009) which used the same syllables and procedures and also suggested only weak support for a speech perception deficit in dyslexia.

Hazan et al. (2013) further investigated identification of consonants from the set /p,b,t,d,f,v,s,z,m,n,sp,st/ and discrimination of sounds varying in in place of articulation (/b/ vs. /d/) and voicing (/b/ vs. /p/). The study included 34 DYS subjects (mean age: 147.3 months) and 25 control subjects (mean age: 146.8 months). Children in the DYS group made more errors in identification but only for a subset of speech sounds, and they made more errors overall in the discrimination task.

In contrast to some of these studies, Ziegler et al. (2009) found speech perception deficits in a group of 19 DYS subjects compared with 18 CA control subjects and 19 RL control subjects. Listeners heard VCV syllables with the vowel /a/ and one of 16 possible French consonants (/p,t,k,b,d,g,f,s,ʃ,m,n,r,l,v,z,j/). The results showed a difference between DYS and control subjects for speech recognition in noise, but no difference for speech recognition in quiet.

Finally, White-Schwoch et al. (2015) tested 112 children using an electrophysiological measure of speech processing (using the syllable /da/ as testing material) with a group of 4-year-old children (N=37; mean age: 54.41 months) and a group of 3-year-old children (N=20; mean age: 43.35 months). They found that poor processing was related to differences in phonological awareness scores, suggesting a possible relationship between speech processing and reading ability. In addition, for a subset of children (N=34) who returned a year later, they found that the earlier neurophysiological measure predicted performance in measures of reading and literacy, again suggesting a link between speech processing and reading ability.

Summary and Research Questions

To summarize, work investigating the relationship between speech perception and reading development, while variable, has not found consistent differences between RD and TD children. However, many of these studies have used paradigms such as categorical perception tasks that do not accurately capture sensitivity to low-level (sub-phonemic) differences in speech, and many have only investigated a small subset of speech sounds, such as stop consonants. Therefore, a more thorough investigation is in order, to clarify the roles of the various processing channels and evaluate whether the classic Fletcher model of speech recognition (Fig. 1) can provide insights into the nature of RDs.

As discussed above and as documented by Miller et al. (1951), it is difficult to analyze a speech perception problem using meaningful speech as testing material due to the context channel, which plays a critical role in the process. The importance of the context channel was obvious to Fletcher (1929), which is

why he broke the problem into parts. In Fletcher's model, contextual processing is the last stage in the speech perception process. Therefore, relatively speaking, phone recognition is a more basic (earlier) layer of speech perception. In turn, accurate phone recognition is important for decoding and other reading skills. This suggests that phone perception may determine the success of reading and comprehension.

Although phonological awareness and decoding—both of which assume accurate speech perception—are viewed as causal factors in RD, there are still studies showing that speech perception deficits do not seem to be involved. However few studies (if any) specifically map out the early phonetic encoding abilities of children with reading difficulties. Hence, in this study, the following questions were addressed:

1. Without access to visual (i.e., letter) and contextual (i.e., word) information, do children with RD show a phonetic encoding deficit?
2. If so, what type of task is most effective in diagnosing RD? What task is most informative about RD regarding perception of specific speech sounds?
3. Do RD and TD children have common or unique phonetic perception patterns (i.e., do they have similar or dissimilar patterns of speech sound confusions)? Alternatively are they idiosyncratic? If so, to what extent?

Two experimental tasks were used to address these questions: (1) the *Syllable Confusion Oddball* (SCO) task, which involves speech sound discrimination, and (2) the *Nonsense Syllable Confusion Matrix* (NSCM) task, which involves speech sound identification, reported orally. This report mainly details the results of the SCO task, but with supplementary data from the NSCM task briefly presented to illustrate key differences between RD and RC children.

SCO Task. For the SCO task, on each trial, subjects hear three naturally-produced speech syllables (CV or VC), where two sounds are the same C (or V) and one is different. Only a C or V was modified on a given trial, not both. For example, listeners might hear /ka, ʒa, ka/. They were asked to identify the position of the oddball syllable. The oddball was always chosen randomly to occur in one of the three positions. The three sounds were always either CV or VC, and the two syllable structures were never mixed within a trial. Critically, the three syllables were always spoken by three different talkers, chosen randomly from a set of 18 mixed gender talkers. Thus, the three CV/VC tokens were *always*

different, due to the talker differences. The children understood the task was to identify the oddball syllable based on the C or V difference and that they should ignore talker and gender differences.

Similar oddball tasks have been used in previous work on RD (e.g., Bradley and Bryant, 1978, 1983), but these studies used real words. As discussed above, the use of real words as testing materials may lead to influence from the context channel (i.e., word meaning) in addition to the auditory channel. In the present study, the testing materials are all maximum entropy (*MaxEnt*) in the SCO task, defined as syllables consisting of all possible combinations in English, with equal probability. MaxEnt syllables represent the full range of phonological differences that may occur. Using materials with no meaningful linguistic content allows us to focus on the contribution of the auditory channel to estimate children's phone identification and discrimination abilities.

The SCO task has extensive coverage of consonants and vowels in English: 24 consonants spanning 15 vowel contexts. The sounds were produced by 18 talkers to better represent the natural variation encountered with speakers of English. Because the children only needed to respond based on the information in the specific tokens, there was no need for them to segment phones from the syllables, or to identify/label them. Hence, the task should be easier, and thus more accurate, than a phonological awareness task. Moreover, there is no influence of the visual channel, since printed materials are not used. Thus, in this experiment, the children had to rely exclusively on the auditory channel.

NSCM Task. The NSCM task complements the SCO task in that it provides confusion data, which are unavailable from the SCO task (since it only identifies which sounds are confusable, not which other sounds they are confused with). In the NSCM task, listeners hear a single CV or VC and are instructed to orally repeat the syllable they heard. The downside of this test is that it requires two transcribers to code the verbal report. This is error prone since the children do not always clearly articulate their response, especially when they are unsure of the identity of the spoken token. Nonetheless, this task provides useful data, missing from the SCO task. In particular, the NSCM task adds value by providing confusion matrix information, which could be used during training sessions and as diagnostic feedback on any change in the child's status. Knowing the degree to which confusions occur could also prove useful to a speech therapist. We report preliminary results from this task in the current paper.

Methods

Participants

Two groups, RD and RC children, participated in the experiment. The RD group had 11 children (seven girls), aged 8 to 10 years. The RC group had six children (two girls), aged 8 to 11 years. This is a typical age range where deficits are discovered, but rarely overcome, during reading development. Interviews of at least one parent were conducted. All the children with RD were recruited from the Urbana *Reading Group*.³ The study was approved by the University of Illinois at Urbana-Champaign IRB. Note that names used in the manuscript are pseudonyms.

Every child passed a pure-tone hearing screening (500Hz, 1kHz, 2kHz, and 4kHz in each ear, at 20 dB SPL), indicating normal hearing ability. This test was repeated at the beginning of each visit, to ensure that there was no temporary hearing loss. There were no known visual, neurological, cognitive, or emotional problems for these subjects. All the children had at least a normal IQ for their age.

To assess their reading abilities, a battery of reading tests were administered including the Woodcock Reading Mastery Tests-Revised (WRMT-R), specifically the Word Identification subtest (WI) and Word Attack subtest (WA), and the grey Oral Reading Test, 4th edition (GORT-4), which included a Fluency score (R-FLU) and Comprehension score (R-COMP; Johnson et al., 2015). For each measure, the children in the RD group scored significantly lower than the children in the RC group (using Welch's t-test): WI ($t(9)=4.34$, $p=0.002$), WA ($t(11)=5.18$, $p<0.001$), R-FLU ($t(7)=4.03$, $p=0.005$), and R-COMP ($t(13)=4.64$, $p<0.001$). For all four reading measures, the RD group scored at least one standard deviation below the RC children, using the criterion of each measure.

Stimuli

Natural speech sounds have more subtle and realistic perceptual cues than synthetic sounds, thus are considered superior for human speech perception tests (Li, 2009). The set of natural sounds that were used for both tasks came from the commercial Linguistic Data Consortium LDC-2005S22 database (Fousek et al., 2004). The database contains a set of all diphone syllables allowed in English (i.e., CV and VC

³ Reading Group: 3011 Village Office Pl, Champaign, IL 61822

syllables) formed from 24 consonants and 15 vowels, spoken by 18 talkers.⁴ Necessarily, some subset of syllables are words, as required by the definition for MaxEnt syllables.

Stimuli were presented without background noise, in random sequence, at the listener's most comfortable loudness level, chosen by the subject at the beginning of each session. The sounds could be replayed as many times as desired, but very few sounds were requested for more than three presentations. Children listened through AKG K240 Monitor headphones (circumaural, 600 Ω) via the laptop's 24 bit sound card. Sounds were processed to remove artifacts (e.g., lip smacks) and loudness variations.

Procedure

Each child participated in the study for up to 10 weeks, for a maximum of two hours per week. They completed one hour of testing using the SCO task every other week. On average, each child completed 1600 trials of the SCO task, with a standard deviation of 548 trials. During each task, to avoid the possibility of fatigue and boredom, children were given five minute breaks for rest and treats, for every ten minutes of testing. Table 3 shows the average number of trials and standard deviation for consonants (row 1) and vowels (row 2) in initial position (column 1) and final position (column 2), averaged over the RD and RC children (e.g., for consonant initial stimuli, the average was 42 and the standard deviation was 19).

The SCO task consisted of a combination of three MaxEnt (i.e., random) syllables (either all CVs or all VCs). The children were asked to point at one of three wooden blocks labeled with the numbers 1, 2, or 3, corresponding to the oddball sound. The response was recorded by the research assistant for subsequent analysis. In the NSCM task, children heard a single syllable and repeated what they heard.

Results

Results for the SCO task are presented first, starting with the results of statistical analyses of the data, followed by a description of the results for individual listeners compared with average performance for the RD and RC groups. Data are organized based on each of the four experimental conditions (i.e., consonant initial [CI], consonant final [CF], vowel initial [VI], vowel final [VF]).

⁴ Instead of International Phonetic Alphabet (IPA) symbols, some figures in this report were generated using Darpabet to represent the phones. Sounds used in this study are presented in Appendix A along with the conversion between Darpabet and IPA.

Regression Analysis for the SCO task

Data were analyzed using logistic mixed-effects models fit using the lme4 package (Bates et al., 2015) in R (R Core Team, 2014) with proportion error (P_e) as the dependent measure. Note there is a simple relation between log-odds ($\log(P_e/1 - P_e)$) and P_e , allowing one to easily convert between them. Baayen et al. (2008) provides a helpful discussion on using mixed-effects models, and Jaeger (2008) discusses the log-odds method.

The model includes three *fixed effects*, defined as discrete binary sets (having elements $\in \mathbb{N}$), which are: (1) Subject Group (RD vs. RC), allowing us to determine whether there is a difference in P_e between the two groups, versus the null hypothesis (i.e., no difference between the two groups); (2) Phone position (initial vs. final), and (3) Phone type (consonant vs. vowel). Fixed effects were numerically coded and centered with a mean of zero, with predictors for main effects of each factor and all two-way and three-way interactions between the factors.

The model also includes two *random effects*, defined as continuous sets (having elements $\in \mathbb{R}$), such as factors sampled from the population: (1) individual listeners and (2) individual phones (i.e., the specific consonant or vowel that the listener heard). Main effects corresponding to these differences are entered as random intercepts in the model. We also included by-subject and by-phone random-effect slopes, which describe interactions with fixed effects in the model. These include by-subject slopes for phone position (i.e., do phone position effects vary depending on the individual listener?), phone type (do consonant vs. vowel effects vary depending on the individual listener?), and their interaction. By-phone random-effect slopes were included for subject group (do differences between RD and RC listeners depend on the specific phone?), phone position (do differences between initial and final position depend on the specific phone?), and their interactions. Lastly, we included a term corresponding to the interaction between subject and phone, allowing us to see whether individual listeners differ in the specific phones for which they make errors. Note that these models do not test for a overall effect of phone, as we already know that errors vary considerably as a function of this factor (i.e., some phones produce more errors than others; Singh and Allen, 2012; Toscano and Allen, 2014).

Likelihood ratio (χ^2) tests were used to determine whether each of the factors above had a

significant effect on P_e .⁵ These tests were performed using nested model comparisons in which factors are added to the model sequentially and we measure whether including the factor significantly improves the model's fit to the data (based on the change in its log likelihood). This provides a way to test significance for both the fixed and random effects in the model. Two sets of likelihood ratio tests were performed, one for fixed effects (including models with all random effects terms) and one for random effects (including all fixed effects terms).

Results summary

A summary of results from the regression analysis for the fixed effects is presented in Table 4, where b is the regression coefficient and SE is the standard error. The largest effect is subject group ($b=1.123$, $SE=0.304$, $\chi^2(1)=9.918$, $p=0.002$), demonstrating that the RD listeners made significantly more errors than the RC listeners, with an average of 17.9% error for the RD group and 6.6% error for the RC group.⁶ There was also a significant effect of phone position ($b=-0.279$, $SE=0.096$, $\chi^2(1)=7.706$, $p=0.006$), with listeners making more errors for sounds in final position (mean error: 14.4%) than initial position (mean error: 12.1%). No other fixed effects or interactions between the fixed effects were significant.

Results for random effects are presented in Table 5. We found a main effect of subject ($\chi^2(1)=983.918$, $p<0.001$), indicating that individual subjects (ignoring RD status) varied in their error rates. We also found an interaction between subject and phone type ($\chi^2(1)=33.472$, $p<0.001$), indicating that subjects differed in the likelihood of C versus V errors. Similarly, we found an interaction between subject and phone position ($\chi^2(1)=33.545$, $p<0.001$), indicating that subjects differed in the likelihood of making errors for sounds initial versus final position. There was also an interaction between phone and position ($\chi^2(1)=4.218$, $p=0.040$), suggesting that the effect of syllable position varied depending on the specific phone. Lastly, we found a three-way interaction between subject, phone type, and phone position ($\chi^2(1)=15.275$, $p<0.001$), indicating that subjects varied in their error rates as a function of both phone type and position within the syllable. Other interactions in the random effects analysis were not significant.

⁵ Note that this test depends on the residuals being Gaussian, which may or may not be the case. Thus, the raw data is displayed in several figures to support these assumptions.

⁶ These mean error rates are computed at the individual trial level. Because some subjects had more trials than others, the subject-level error rates are slightly different (mean RD: 18.8%, mean RC: 6.7%).

In summary, the statistical analyses confirm the prediction that the RD listeners perform significantly worse in the SCO task than the RC listeners, and they reveal that there are idiosyncratic differences among individual subjects in which types of phones lead to errors. In the next section, we explore these results in greater detail, examining both the group differences (RD vs. RC performance) and individual differences between subjects.

Sorted Error Plots

Given the difference in errors between the two subject groups, and the finding that individual subjects make different errors based on phone type and position, results are visualized using *sorted error plots*. To illustrate how these graphs are organized, consider the case of CI stimuli as shown in Fig. 2. The ordinate values are the phone probability of error, on a log % scale. The abscissa of the graph represents the phones, sorted by their RC-average error. To quantify the differences in performance for the RC and RD subjects, the averages of each phone, for the RD (solid blue) and RC (dashed grey) groups, are shown. Also shown for reference are the errors of two typical RD subjects, RD-Alina and RD-Angela (dashed lines). The first abscissa tick represents the consonant with smallest RC-average error (/d/), while the second tick represents the consonant with second smallest RC-average error (/h/), and so on. For the RC children, the lowest errors begin around 3% and monotonically increase to around 10-15% (for /s,ð/). The error bars are the standard deviation for the RC-average.

Error Ratios. Another useful way to visualize the differences between the RC and RD subjects is to examine the error ratio, as a function of phone, between individual RD listeners and the RC-average. Figure 3 displays the log error ratios for each RD subject, relative to the RC-average, for the four conditions in the experiment (CI, CF, VI, VF). As the figure shows, most of the RD subjects' errors are 2–10× those of the RC-average, with a few points outside this range. A few subjects (e.g., RD-Shauna) have many ratios close to the RC-average (see the figure caption for details), though some phones still show higher ratios for these subjects. The figure reveals a striking separation between the RC and RD children, with large error ratios for individual RD listeners relative to the RC-average error (grey line).

Consonants in syllable-initial (CI) position. Next, we examine the sorted error plots for individual RC and RD listeners. Results for CI sounds are shown in Figure 4. As in Figure 2, the grey (dashed) curve is the RC-average of the sorted probabilities of error. Those averages range from 3–15%. A

limitation of plotting error on a log scale is that we cannot present zero phone error, which is common in the RC group. Thus, we added histograms to show the number of zero-error sounds for the RC and RD subjects. These zero-error phones influence the RC-average error. Generally, there are one to three children (out of 6) from the RC group with zero-errors for each phone. The solid blue curve shows the RD-average. Probabilities of error for RD subjects ranged roughly between 7% and 25%.

In upper panel of Figure 4, the points show the errors for each individual RC subject. Overall, the RD average error is at the upper bound of the RC individual error points, indicating that the worst performance of a phone for RC subjects is almost always better than the average performance of RD subjects. The lower panel shows errors for individual RD listeners, illustrating that many children in the RD group (e.g., RD-Alina, RD-Angela, RD-Edward, RD-Latisha, RD-Laura, RD-Shauna, RD-Tony) struggle with discriminating all consonants in the initial position, starting with the lowest at 7% error. The errors for these six RD subjects, for all consonants, are near or above the average of the RD group, far worse than the RC-average error. A few RD subjects did as well on some consonants as the average of the RC group (e.g., RD-Norene, RD-Teddy, RD-Tina), but these are notable exceptions, as may be seen in the figure (the RD data points below the dashed grey line).

As previously shown in Figure 3, the RC group had between 3–5× (or better) performance in discriminating consonants in syllable initial position than most, but not all, of the children in the RD group. RC-Anton had no error for 10 out of the total 24 consonants. RC-Carly also had zero-error for 7 out of the total 24 consonants. The sorted error curves for RC-Anton, RC-Evan, and RC-Carly were the lowest among all the subjects, with probabilities of error ranging from less than 2% to less than 20%. RC-Bob and RC-Miguel, with normal reading ability, had similar errors to RD-Norene and RD-Teddy. The probabilities of error for these subjects ranged from 3% to 30%. Thus, there are a few *cross-over subjects* in both groups. In addition, RD-Laura and RD-Edward had large differences in error across consonants, indicating that some consonants were much more difficult for them to perceive than others. Sorted error plots for each RD subject show that, between them, RD-Laura had the smallest intercept, meaning there are lower errors for the lower ranking phones.

Consonants in syllable-final (CF) position. Figure 5 show results for consonants in final position, in the same format as Figure 4. The top panel shows that the RD average error is at the upper bound of the individual RC data. As seen in Figure 3, the error ratio between the RC and RD average curves is 3–5×.

Thus, CI and CF sounds are similar in terms of their effects on the two subject groups.

Among individual subjects, RD-Alina had more than 10% error for almost all consonants in final position. RD-Latisha, RD-Norene, RD-Edward, and RD-Angela are also on the slightly higher error side. RC-Anton had no trouble discriminating 10 out of 24 consonants, with the highest probability of error for these sounds less than 10%. RC-Joanna, RC-Evan and RD-Teddy performed with less than 20% error. RC-Joanna had no error for 7 out of 24 consonants. The highest error rate for RC-Bob was slightly greater than 20%. RC-Miguel and RD-Shauna had a slightly higher error, ranging from 5 to 30%. Also, RC-Carly, RD-Alina, and RD-Angela had high error rates for some phones and very low error rates for others, meaning they showed more abrupt increases in perceptual difficulties across consonants than other children. Errors for RD-Latisha, RD-Norene, and RD-Edward are stable for different phones, meaning every phone caused similar difficulties. RC subjects, along with RD-Shauna and RD-Teddy had relatively uniform smaller probabilities of error for all consonants. For CF sounds, RD-Shauna and RD-Teddy are the cross-over participants. Overall, there are differences between the individual RD subjects, showing idiosyncratic errors. There are also individual differences for subjects between their CI and CF errors: Data collected from RC-Carly for CF sounds revealed a minimum probability of error of around 3%, while for CI sounds, there was zero-error for 7 out of 24 consonants.

Vowels in syllable-initial (VI) position. Figure 6 shows data for vowels in syllable initial position in the same format as Figure 4. Previous high performers like RC-Anton and RD-Teddy still outperformed everyone, having between 2% and 20% error. RC-Bob showed improved discrimination of vowels in initial position, compared with discrimination of consonants in initial position. RD-Latisha struggled the most with discriminating vowels in syllable-initial position with an error rate of 20% or greater. Along with RD-Alina and RD-Latisha, RD-Tony and RD-Edward were among the worst performers, with probabilities of error ranging from 10% to slightly higher than 40%; while RD-Angela, RD-Laura, and RD-Norene along with RC-Joanna, RC-Evan, RC-Carly and RC-Miguel were in the middle with 2–30% error.

Vowels in syllable-final (VF) position. Figure 7 shows results for vowels in final position, in the same format as the previous figures. As in the other conditions, the VF sounds show a clear separation between the RD and RC groups. RC-Anton had the lowest error of all subjects, with zero-error for 8 of the 15 vowels; the highest error rate was 7%. RC-Joanna was the second best, with maximum error for all vowels less than 10%. The data across all conditions showed that RC-Joanna's phone discrimination was

better when the phone was in syllable-final position, whether the phone was a consonant or a vowel. The rest of the lower error subjects were RC-Evan, RC-Carly and RC-Bob. RC-Miguel had the highest error among all children, starting at 30%. The rest of the high error group were RD-Tony, RD-Teddy, RD-Latisha, RD-Edward, RD-Alina, RD-Angela and RD-Norene.

NSCM results

The results of the SCO task reveal substantial differences between the RD and RC subjects and show a large number of individual differences between subjects. The data from the NSCM task provide a useful way to capture these individual differences. Here, we present a few examples of the NSCM data to illustrate this point. As summarized above, in the NSCM task, subjects heard a single MaxEnt syllable (CV or VC) and repeated it back. Two expert transcribers wrote down which phone they heard the subject produce. This results in a *confusion matrix*, which codes the confusions. While the effect is small, errors in the NSCM task were slightly smaller than those in the SCO task. It is not clear why, and this was unexpected.

The data from this task are analyzed as directed graphs, which provide a graphical method for summarizing a confusion matrix. In these graphs, nodes represent individual phones that the listener hears, and connections between nodes depict the listener's confusions. Connections from the node back to itself are correct responses. Connections to other nodes are errors, with the percentage written above each connection indicating how often that particular confusion was made.

First, we examine the confusion matrices collected for the two best RC subjects, RC-Anton and RC-Evan. Then, we investigate CI and CF sounds for RD-Norene who is close to the RD average in performance. As we shall see in these comparisons, the RC subjects make few errors, while RD-Norene makes many more errors. Moreover, the directed graphs for each subject's data capture the confusions made for each phone. Given the confusion matrix, interventions could be developed based on the specific phones for which an RD subject needs the most help. These methods could also be used to track improvements in the subject's phone recognition over time.

RC subjects. Figure 8 shows the confusion matrix data for RC-Anton, who has the lowest error of the RC group. Overall, the graph shows almost no error, as indicated by the nodes without connections to other nodes in the graph. A pruned graph highlighting a subset of this full error graph is shown in Figure 10. Confusion data for RC-Evan, who has the next lowest error, are shown in Figure 9; low-level errors for

RC-Evan are shown in the right panel of the pruned graph (Fig. 10).

The pruned graphs reveal a number of interesting details about the low-level errors for the RC subjects. For example, for RC-Anton (left) on the top-left of the pruned graph, there is a single arrow, looping back to the node labeled /d/, indicating that this sound is recognized correctly 99% of the time (i.e., 1% error) with a threshold around chance. A more interesting case is /ð/, which has only 62% correct responses and is confused with /θ/ (13%), /v/ (8%), and /w/ (5%). /θ/ has a higher score of 74% correct, having 9% confusions with /f/ and /θ/. Presentations of /f/ are almost entirely confused with /θ/ (27% of the time). This is RC-Anton's largest error phone, which is common for all RC listeners. Another common error for the RC group, that Anton does *not* make, is confusing /f/ as /v/.

RD subjects. The RD subjects have, in general, very complex graphs, with many errors between consonants. It is instructive to compare CI and CF sounds for a single listener. This is illustrated in Figures 11 and 12, which compare the graphs for CI versus CF sounds for RD-Norene. More data like these need to be analyzed in detail in follow up studies; they are shown here simply to demonstrate how they supplement and amplify the SCO results. The large number of errors, and the specific type, would be very helpful to a speech therapist. It would be very interesting to establish if these errors are correctable, following therapy.

Discussion

A valid theory of reading is the key to understanding reading disability. Without understanding of the underlying causes of RD, there can be no successful diagnosis or treatment. But every theory must be driven by experimental data. Theories about reading ability, beginning in the 1950s, and were based on the widely held view that *phonological awareness* was the key to understanding reading, due to the observed high correlation between phonological awareness and RD. Moreover, models of reading emphasize the importance of decoding skills in leading to read, providing a viable approach for RD interventions.

However, any intervention based on phonological awareness or decoding skills assumes that RD children have intact speech perception (i.e., phone encoding). As discussed in the Introduction, many studies have attempted to experimentally link RD and speech perception. These experiments were largely unsuccessful, and it is now clearer why they gave negative results. Most experiments that have aimed to link speech perception and RD have emphasized phoneme categorization and have often used stimuli that incorporate information from the context channel (e.g., meaningful words). Hence, they emphasized tests

involving phonemes (the smallest unit of meaning) instead of phones (the smallest unit of speech).

Based on our present understanding of speech perception, as outlined in Fig. 1, we can see that low-level speech perception may also play a critical role in reading. This model is now supported by the experimental evidence presented here and work demonstrating that listeners are highly sensitive to sub-phonemic (i.e., phone-level) differences in speech (Li and Allen, 2011; Singh and Allen, 2012; Toscano and Allen, 2014). The results from the current study confirm that deficits in phone-level perception are related to RD. Below, we discuss the possible sources of this deficit, and we summarize how the two tasks used in this study provide insights into this issue.

Possible sources of RD speech perception errors

The results of this study suggest a similarity between RD children and hearing impaired listeners. RD children typically have normal hearing and may have normal speech production. Thus, on the surface, there is no obvious reason to question whether they might have a speech perception problem. But given the experimental results presented here, we now see that there are large differences between RC and RD children in their speech perception abilities.

It also seems clear from phonological awareness data, that children with RD develop problems early, before first grade, which we view as related to a failure to learn to discriminate a subset of consonants and vowels during the time that normal developing children learn to recognize speech. It is unclear what the source of these speech perception deficits is, but one plausible explanation is a lack of exposure to speech sounds during early development. Given the idiosyncratic nature of the errors, cochlear hearing loss does not seem to be a likely cause.

It is known, however, that episodic middle ear problems can cause up to a 50 dB hearing loss, for months at a time (Williams and Jacobs, 2009). Perhaps this is a major source of the problem, but the impact is not obvious because most speech sounds can be adequately discriminated, thus speech perception appears to be normal. Yet, when asked to discriminate individual sounds, RD children make many more errors than RC children (Fig. 3). If temporary middle ear loss is the main cause, then it seems likely, given their normal cochlear function and normal cognition, that speech perception training, highly focused on the specific errors that the listener makes, might dramatically improve their phone discrimination, and thus their reading. Only with early detection, along with the proper diagnostic feedback, and drilling on the high

error sounds, can we determine if this will resolve the problems. There is significant evidence that given enough resources, reading problems can be resolved. But with no resources and no diagnostics, these subtle problems remain untreated.

Results from the SCO and NSCM tasks

The two tasks used in the current study (SCO and NSCM) nicely complement each other. The SCO task can quickly determine which phones cause errors, but it does not indicate which sounds they are confused with. In contrast, the NSCM task gives a detailed map of the exact nature of the errors, in the form of a confusion matrix (directed graph). It should be possible for a speech therapist to use this information to improve phone recognition for RD children. It would be even more encouraging if, after improving their speech recognition scores, reading ability improves. This suggests experiments for future research.

The results of the SCO task also clearly demonstrate how much worse the RD children performed compared with the RC children in phone recognition. Previous work has found mixed evidence for speech perception deficits in children with dyslexia (Hazan and Adlard, 1998; Ziegler et al., 2009; Messaoud-Galusi et al., 2011). However, from our results, we conclude that notable phonetic deficits exist for RD children compared with children who have normal reading ability. As shown by the sorted error plots, in general, the RC group performed much better than the RD group on the SCO task, with more zero-error phones and lower probabilities of error than the RD children.

The phonetic encoding process was engaged, perhaps even taxed, during the SCO task. The children were not told whether the change of phone was in the syllable-initial position or in the syllable-final position. They were presented with utterances with the only instructions being that they would hear three syllables and then should find the one that had a change in sound structure. It seems likely that the children with RD struggled with mismatched phone representations during the SCO task, requiring greater effort to store all the information they heard in memory, instead of processing the phones easily and correctly, without effort. Some of the RC children had the same error magnitude, but as a group, they outperformed the RD children. More experiments on the SCO task with various numbers of potentially confusing phones (e.g. a triad, quartet, or quintet of syllables) would be needed to fully characterize reasons why the 3-trial SCO task had larger error than the single-trial NSCM task.

Outliers in the phonetic encoding tasks

Although the RC group performed significantly better than the RD group in the SCO task, not all RD subjects performed worse than RC subjects. Based on close inspection of Figs. 4–7, RD-Norene and RD-Teddy performed at the RC-average error for consonants in initial position, RD-Shauna and RD-Teddy performed at the RC-average error for consonants in final position and vowels in initial position, and RD-Shauna performed at the RC-average error for vowels in final position. These outliers in the RD group all demonstrated normal phone recognition, similar to the RC children. Thus, there are factors other than weakness in phonetic perception that must contribute to reading disorders for these children.

Conclusions

The results of the current study demonstrate that the model of speech perception in Figure 1 can help us understand reading difficulties: accurate phone encoding at early stages of processing is a pre-requisite for other steps in the process. If children can complete this fundamental step, then they can learn to read. This is the take-home message of the current study, and it is confirmed by the results presented above. RD subjects made considerably more phone recognition errors than RC subjects, and individual differences were observed in the type of phone (consonant vs. vowel) and syllable position (initial vs. final) that caused errors. Overall, the data suggest that speech perception is a critical factor in reading development. In conclusion, to answer our initial questions:

1. Without access to visual (i.e., letter) and contextual (i.e., word) information, do children with RD show a phonetic encoding deficit? **Yes.**
2. If so, what type of task is most effective in diagnosing RD? **SCO.** What task is most informative about RD regarding perception of specific speech sounds? **NSCM.**
3. Do RD and TD children have common or unique phonetic perception patterns (i.e., do they have similar or dissimilar patterns of speech sound confusions)? Alternatively are they idiosyncratic? If so, to what extent? **Errors are idiosyncratic to a large extent.**

Author Contributions

Author JA designed the experiment and wrote the code for collecting the SCO data (c. 2005). CJ initiates a relationship with *The Reading Group, Urbana IL* and collects the data, with help from several graduate students. JL analyzes the data using ANOVA in her doctoral dissertation (c. 2017). JT recommends, and then provides an extended logit statistical analyses; YW and JA finalized the thesis, and JL graduates; YW writes the present manuscript, including an extended analysis, introducing Figs. 2-7. JA and JT proofread the manuscript, and YW submits.

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Table 1

Table of abbreviations.

TD	typically-developing
RC	reading control
RD	reading disabled or reading disability
SCO	syllable confusion oddball task
NSCM	nonsense syllable confusion matrix task
CI/CF	consonant in initial/final syllable position
VI/VF	vowel in initial/final syllable position
WI	Word Identification subtest
WA	Word Attack subtest
WRMT-R	Woodcock Reading Mastery Tests-Revised
R-FLU	Reading Fluency score
DYS	Dyslexia or dyslexic subjects
CA	Chronological age matched subjects
RL	Reading level matched subjects
dB	decibel
SNR	signal to noise ratio
AI	Articulation index

Table 2

Definitions of related concepts.

Phone	speech sound token; smallest sound unit of speech (i.e., individual consonants and vowels)
Phoneme	set of phones of the same type; smallest unit that distinguishes meaning
Syllable	combination of any number of consonants (C) and a vowel (V), such as V, CV, and VC
Word	meaningful syllable sequence (spoken or written)
Maximum entropy syllable	syllable constructed by random selection of consonants and vowels; abbreviated <i>MaxEnt syllable</i>
Phonological awareness	the metalinguistic skill of attending to, judging, rhyming, blending, segmenting, and manipulating spoken words, syllables, phonemes, or phones (in the present study, use of the term is restricted to phones in non-words)
Phonetic encoding	the auditory ability of hearing, perceiving, and categorizing phones (speech sounds)
Articulation	recognition of syllables having no meaning; based on Fletcher's <i>Articulation Index</i> model
Intelligibility	recognition of syllable sequences having defined meaning (i.e., words)

Table 3

Average number of trials and standard deviation for CI, CF, VI, and VF stimuli.

	Initial	Final
C	42(19)	44(17)
V	43(19)	45(15)

Table 4

Summary of fixed effects in logistic regression analysis. There are three fixed variables: Group: {RC, RD}; Phone Position: {Initial, Final}; Type (see Appendix A1): {Consonant, Vowel}. The parameter b is the regression coefficient (i.e., slope) with respect to each fixed effect, and SE is the standard error of the regression estimate. χ^2 values are from the likelihood ratio tests (see text), and p is the p -value for those tests.

<i>Fixed Effects</i>	<i>b</i>	<i>SE</i>	$\chi^2(1)$	<i>p</i>	<i>Sig. Level</i>
Group: RC, RD	1.123	0.304	9.918	0.002	**
Phone Position: Initial, Final	-0.279	0.096	7.706	0.006	**
Phone Type: C,V	0.057	0.113	0.320	0.572	
Phone Position \times Group	-0.217	0.191	1.213	0.271	
Phone Position \times Phone Type	-0.054	0.160	0.326	0.568	
Group \times Phone Type	0.013	0.192	0.013	0.910	
Group \times Phone Position \times Phone Type	-0.344	0.312	1.178	0.278	
Significance codes	$p < 10^{-3}$	***;	$p < 10^{-2}$	**;	$p < 0.05$ *

Table 5

Summary of random effects in logistic regression analysis. There are two random effects: Subject: {subjects within each group (RD, RC)}; Phone: {see A1}; along with their interactions with phone position, phone type, and group.

<i>Random Effects</i>	$\chi^2(1)$	<i>p</i>	<i>Sig. Level</i>
Subject	983.918	$< 2 \times 10^{-16}$	***
Phone \times Phone Position	4.218	0.040	*
Subject \times Phone Position	33.472	7×10^{-9}	***
Subject \times Phone Type	33.545	7×10^{-9}	***
Phone \times Group	1.768	0.184	
Phone \times Group \times Phone Position	0.144	0.705	
Subject \times Phone Position \times Phone Type	15.275	9×10^{-5}	***
Subject \times Phone	0.403	0.526	
Significance codes	$p < 10^{-3}$	***;	$p < 10^{-2}$ **; $p < 0.05$ *

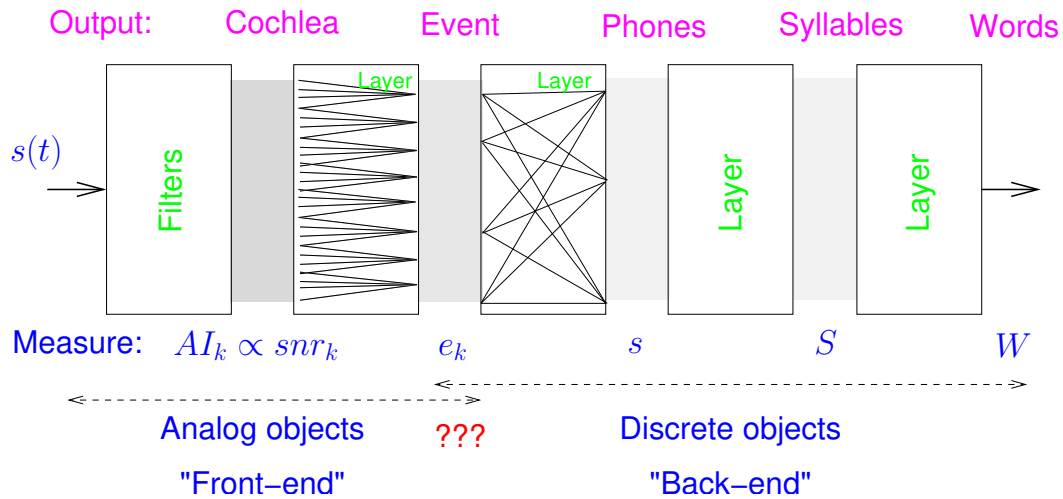


Figure 1. Model block diagram summary of human speech recognition, based on Fletcher (1929). At the top of each block is a label that identifies the physical process. The equations below the boxes indicate the probability measure defined at that level. Speech $s(t)$ enters on the left and is processed by the cochlea (first block), breaking the signal into a filtered continuum of band-passed responses. The output of the cochlea is characterized by the specific AI_k , a normalized signal to noise ratio (SNR), expressed in dB units. The second box represents the work of early auditory areas of the brain, which are responsible for event identification in the speech signal, such as onset transients (Li and Allen, 2011). The third block puts these basic events together, defining phones. The remaining blocks account for context processing (Allen, 2005). The formulas for the measures are discussed in Allen (1996, 2005). (color online)

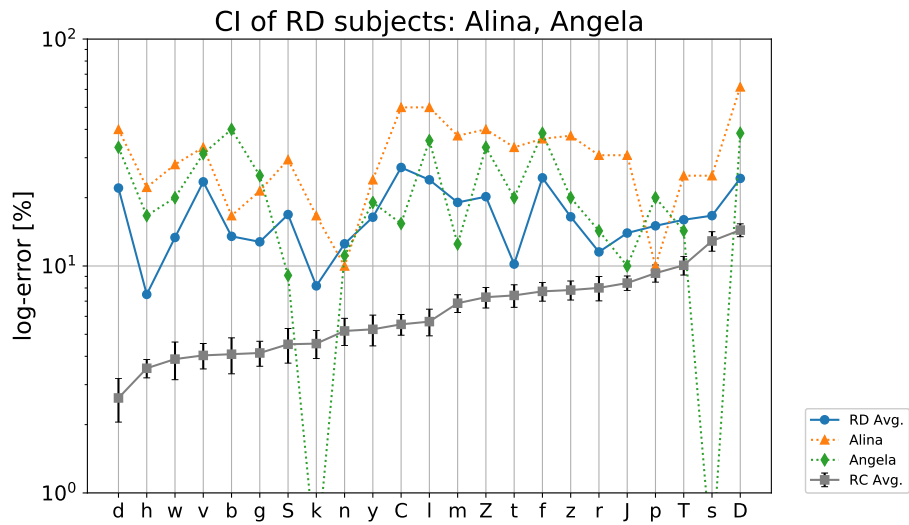


Figure 2. Sorted error for RD- and RC-averages, consonant initial sounds. The grey dashed curve shows the sorted RC-average error. Error-sorted phones are along the abscissa, with the lowest error on the left (/d/) and the highest error on the right (/D/, i.e., /ð/). The ordinate log scale error is in [%]. Alina and Angela are also shown, as two typical RD subjects. This same abscissa order is also used for Figs. 4–7. The standard deviation is shown for the RC-average subject, superimposed on the grey line. Note that the RC-subjects have a small standard deviation about the RC-average mean. Note also how the RD-average (solid blue) is approximately constant, between 1-2%. This uniform error, independent of phone order, is a property of all the RD subjects, but not the RC-average subjects, who show a gradual slope, going from around 3% to 15% error. (color online)

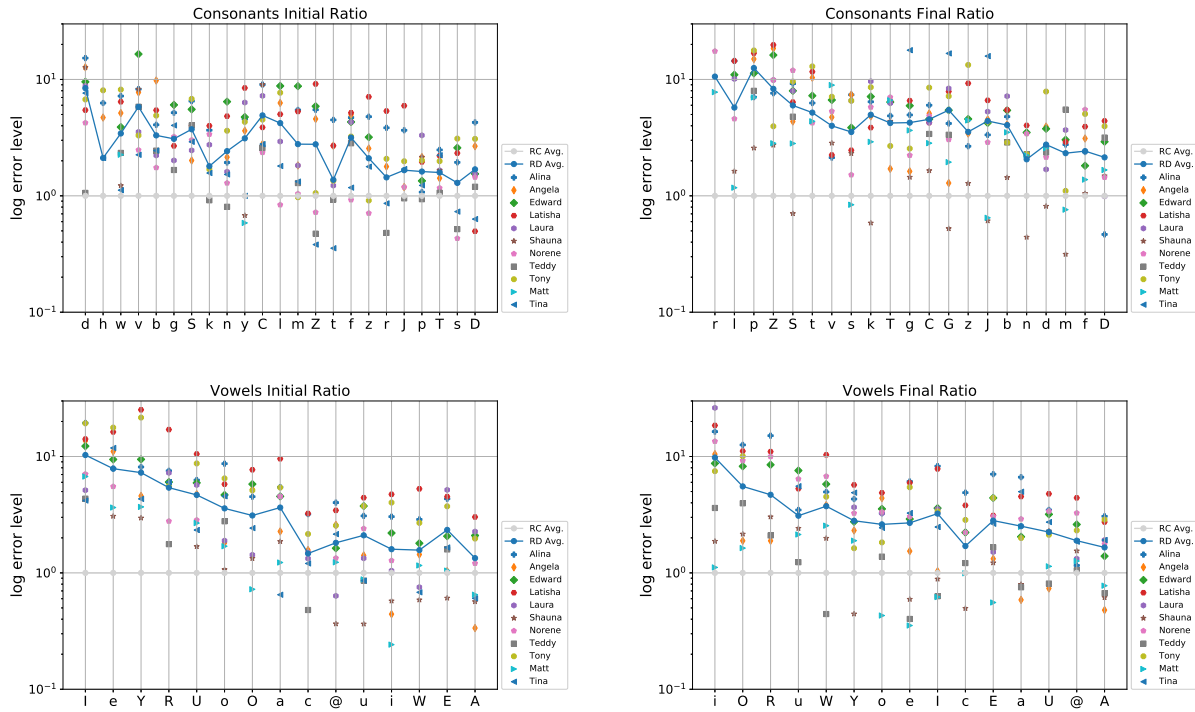


Figure 3. Probability of error ratios of individual RD subjects (colored points), relative to the RC-average (grey line). The ratios (points) are well separated from the RC-average, starting around 10 on the left, and ending around 1.5 on the right. There are a few cases where the RD subjects fall close to RC-average (grey line), and a few subjects fall below a ratio of 1, such as RD-Shauna and RD-Teddy for CF stimuli, RD-Shauna and RD-Norene for CI, RD-Shauna and RD-Teddy for VI, and RD-Shauna for VF. When a subject has a few consonants that are better than the RC average, it is expected there will be other sounds above one (e.g., if a subject always picked the same sound, it would have zero error, forcing 100% error for all other sounds). (color online)

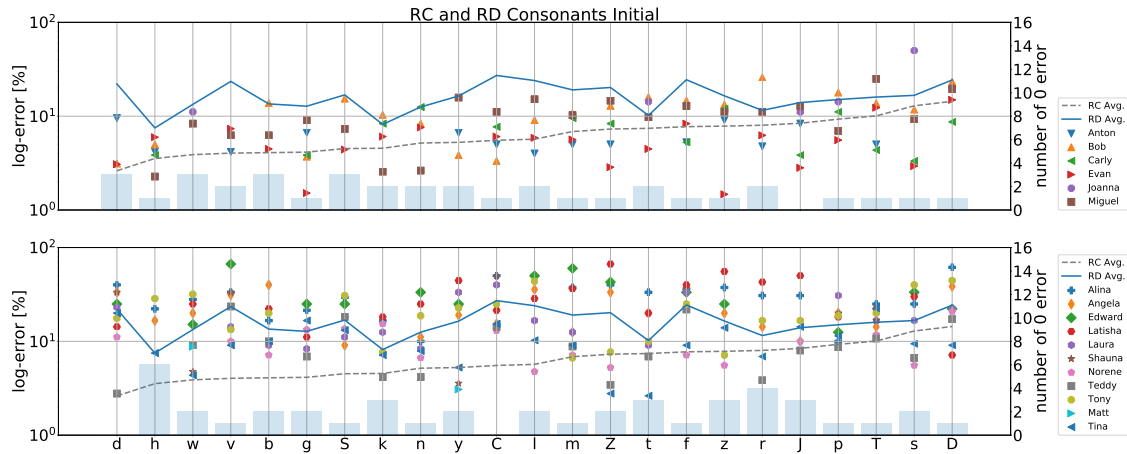


Figure 4. Sorted error for RD and RC subjects for CI sounds, following the same format as Fig. 2. The upper panel is the sorted error plot for the RC group. Data points show each RC subject’s error. The histogram indicates the number of RC individuals who had 0 CI error. Note that the RC group has approximately half the number of children (6) as the RD group (11). Also, note how the RC points mostly lie below the RD-average (blue solid line). The lower panel is the sorted error plot for the RD Group. The dashed grey line represents the RC-average error for CI sounds, while the solid colored line is the RD average error (same as the upper panel). Data points show each RD subject’s error, and the histograms give the number of individuals with 0 error for the CI phones. Note how the RD points mostly lie above the RC-average (grey dashed line). (color online)

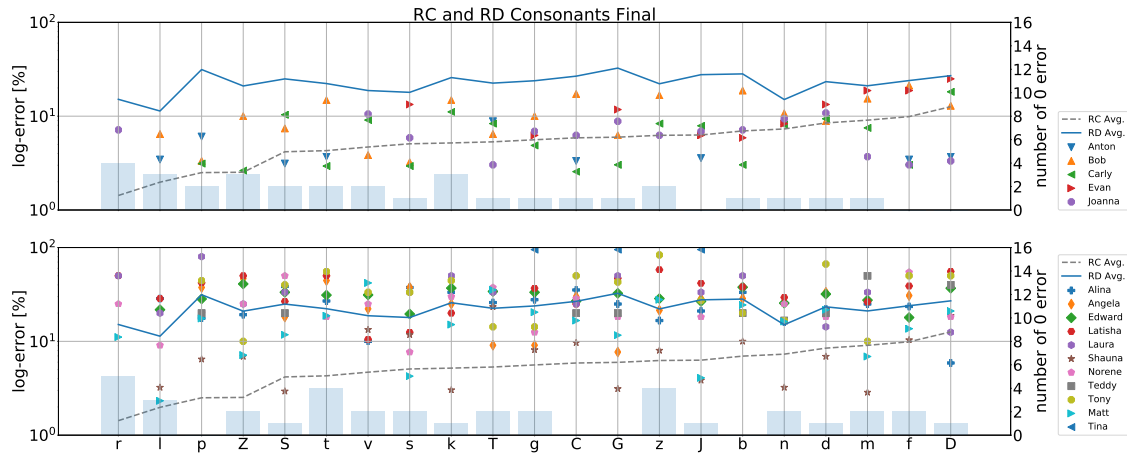


Figure 5. Sorted error for RD and RC subjects, for CF sounds, in the same format as Fig. 4. The lowest RC-average error phone on the left is /r/, and the highest error phone on the right is /ð/. As for CI sounds, note how the RD-errors are nearly constant. (color online)

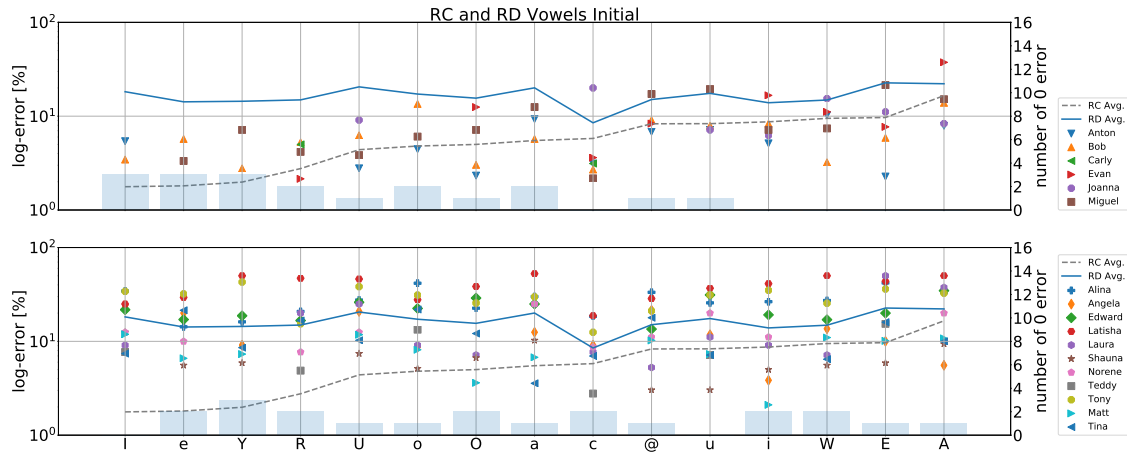


Figure 6. Sorted error for RD and RC subjects, for VI sounds, in the same format as Fig. 4. The lowest RC-average error phone on the left is /i/, and the highest error phone on the right is /a/. (color online)

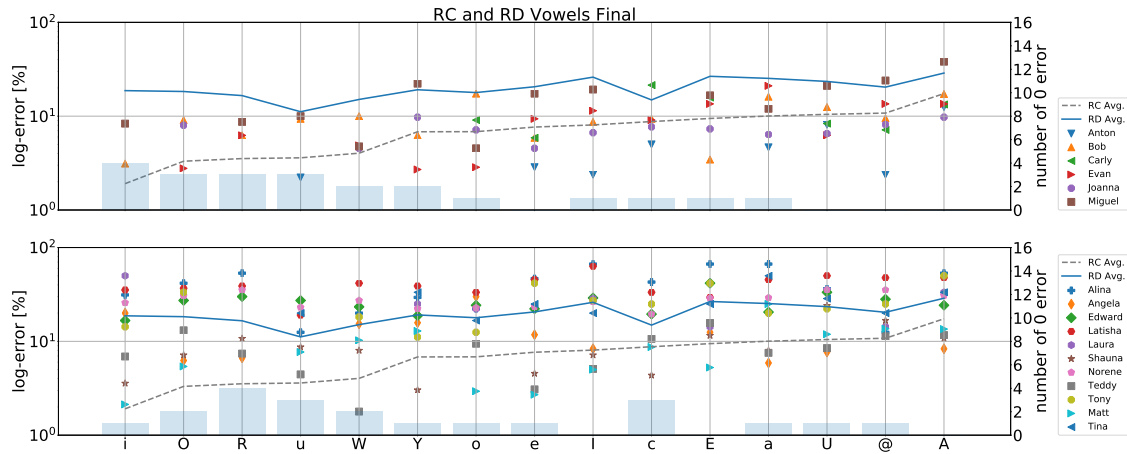


Figure 7. Sorted error for RD and RC subjects, for VF sounds, in same format as Fig. 4. The lowest RC-average error phone on the left is /i/, and the highest error phone on the right is /a/. (color online)

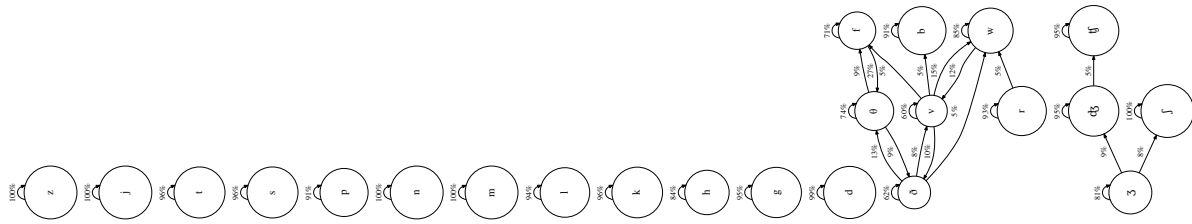


Figure 8. Directed graph for RC-Anton for CI sounds in the NSCM task. RC-Anton made less than 10[%] error on all the sounds other than /ð/ and /θ/. High-error sounds are shown as smaller circles. These three high error sounds are detailed in Fig. 10 (left).

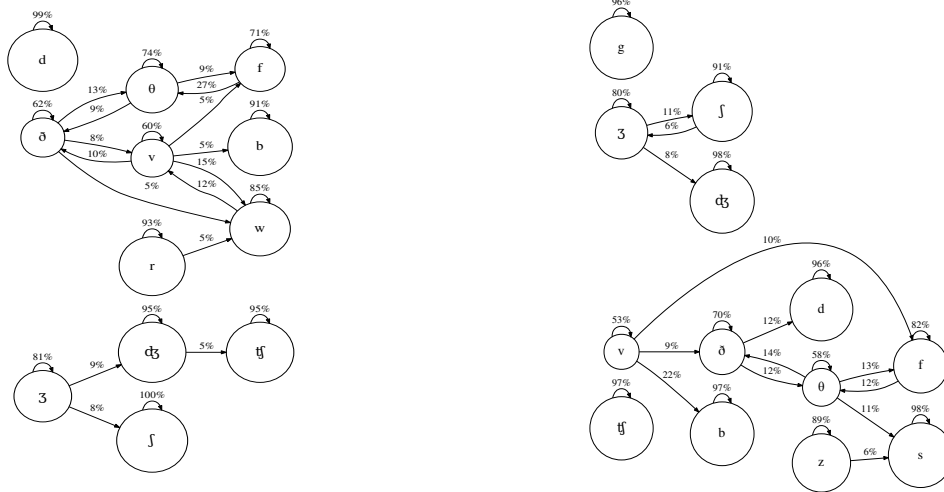


Figure 10. Pruned directed graphs for RC-Anton (left) and RC-Evan (right) for CI sounds. In the pruned graphs, the low error tokens have been removed, and the directed graphs are displayed vertically for improved readability. Smaller circles indicate larger error, such as for /ð,v,ʒ/ (left) and /ʒ,v,ð,θ/ (right).

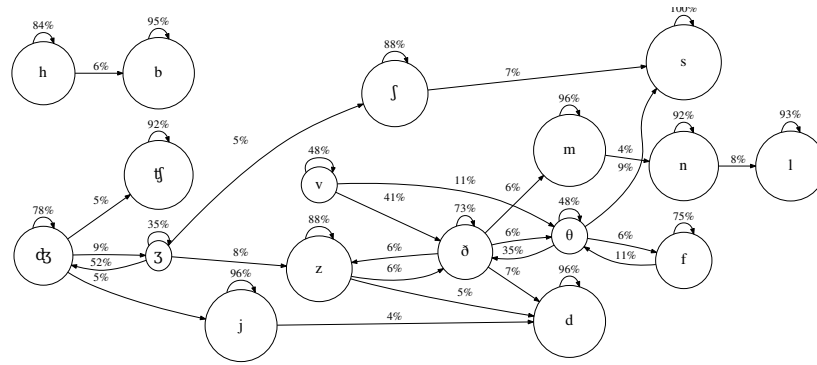


Figure 11. Directed graph for RD-Norene for CI sounds. The number of errors, along with the detail, should be very helpful to a speech therapist, who could concentrate on the most important high error sounds (the smaller circles). It would be very interesting if these errors are correctable, following therapy. It would be even more interesting if correcting these errors would lead to improved reading success.

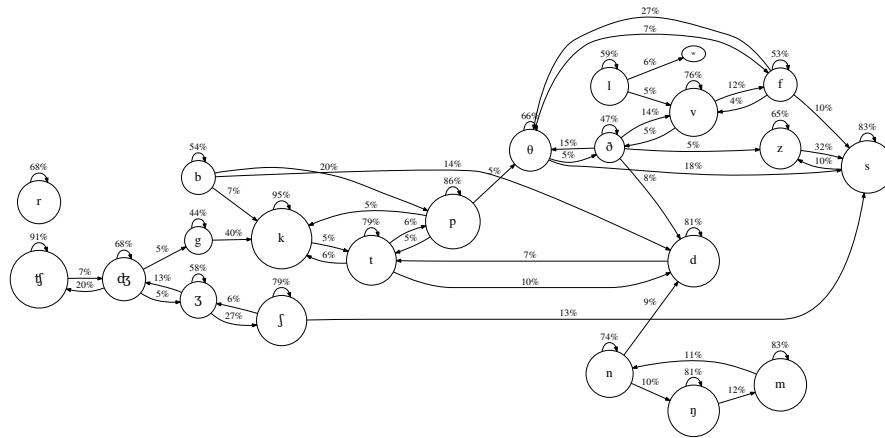


Figure 12. Directed graph for RD-Norene for CF sounds, showing a large number of CF errors compared to most of the RD subjects. This shows the overall poor discrimination of CF sounds. The CF scores are much worse than RD-Norene's CI scores shown in Figure 11.

Appendix

Table A1

Conversion from Darpabet to International Phonetic Alphabet for LDC unvoiced consonants, voiced consonants, and vowels.

Unvoiced Consonants		Voiced Consonants		Vowels		
Dbet	IPA	Dbet	IPA	Dbet	IPA	L/T
C	tʃ	D	ð	@	æ	
S	ʃ	b	b	A	ʌ	T
T	θ	d	d	E	ɛ	L
f	f	g	g	I	ɪ	L
h	h	J	ɟ	O	ɔɪ	
k	k	l	l	R	ɜ	
p	p	m	m	U	ʊ	L
s	s	n	n	W	aʊ	
t	t	r	r	Y	aɪ	
H	ʌ	Z	ʒ	c	ɔ	T
		G	ŋ	a	ɑ	
		v	v	e	e / eɪ	T
		w	w	i	i	T
		y	j	o	o / oʊ	T
		z	z	u	u	T
					ə	L