Behavioral Science Institute
Master of Science Thesis

Why Dyslexia Appears As It Does: The View of Interaction Dominant Dynamics on the Cognitive Deficit of Dyslexia

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Abstract

It has long been thought that there was a 'hump' in the distribution of reading performances of dyslexics and non-dyslexics. Reading ability would be bimodally distributed, with the specific, qualitatively distinct reading disorder appearing as the extreme lower tail. However, research shows that reading performance of dyslexic children and adults lies on a continuum with that of normal readers. Nevertheless, the large variety of theoretical accounts on the causes of dyslexia in distinct mental components in the brain implies that dyslexia is still seen as a qualitatively distinct disorder, contradicting the evidence for a continuum of reading performances. There is already evidence from research on skilled readers, that the assumption underlying the idea of distinct mental components in the brain – *component dominant dynamics* – does not hold (Holden, Van Orden, Turvey, 2009). Instead it is shown that skilled reading originates from *interaction dominant dynamics*. We hypothesize that this view is also applicable to the reading performances of dyslexics. This would 'solve' the contradiction present in current research and it could explain the continuum. The shape of response time distributions can supply information about the types of dynamics in a system. Therefore we looked at response time distributions from a word-naming task presented to 20 dyslexic children and 23 non-dyslexic children from 6th grade of primary school. Results showed that most dyslexic children generated inverse power-law distributions, which is indicative for complex and less-skilled behavior. Non-dyslexics generated more lognormal behavior, which is indicative for more skilled behavior. Both types of distributions reveal the existence of interaction dominant dynamics during reading performance. The results imply that a fundamental revision is needed in the theoretical framework underlying the study of dyslexia.

Keywords: dyslexia, interaction dominant dynamics, response time distributions

Why Dyslexia Appears As It Does:
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Dyslexia is a reading disorder defined by difficulties with accurate and/or fluent word recognition and poor spelling in the absence of sensory impairments, low intelligence, or lack of educational opportunities (Pennington, 2009, p.82; Lyon, Shaywitz, & Shaywitz, 2003; SDN, 2008). Dyslexia is the most prevalent specific learning disorder; an estimated 6-17% of the school-age population is classified as having dyslexia, depending on criteria on the severity of reading difficulties (Fletcher, 2009). Over the past four decades the reading disorder is widely studied by researchers from all over the world in order to unravel the nature of the disorder, possible underlying causes, and effective remediation.

With respect to the nature of the disorder, there has long been the idea that dyslexia is a biologically coherent disorder that is distinct from other, less specific disorders (Rutter & Yule, 1975). In the study of Rutter and Yule, they found that there was a 'hump' in the distribution of reading scores at the bottom of the normal curve. Based on these findings they argued that reading ability is bimodally distributed, with the specific, qualitatively distinct reading disability appearing as the extreme lower tail of the distribution. However, unlike the results from the Rutter and Yale study, international epidemiological studies have shown that dyslexia is dimensional and exists as the lower end of a normal *continuum* (Jorm et al., 1986; Rodgers, 1983; Shaywitz et al., 1992). Shaywitz et al. (1992) argued that the results of their study indicate that no distinct cutoff point exists to distinguish children with dyslexia clearly from children without dyslexia and that deciding on which point on the continuum a disorder resides is very arbitrary. According to them, the differences in outcomes between their study and the study of Rutter and Yule could be explained by methodological concerns in the study of Rutter and Yule. In short, there is compelling evidence that scores of reading performance of dyslexics and non-dyslexics[1] lie on a continuum and that dyslexia cannot be viewed as a qualitatively distinct disorder (Fletcher, 2009). In 1992, Shaywitz et al. already concluded that these results support the need for a fundamental revision in the theoretical framework underlying the study of dyslexia. But has this revision really taken place? Can we conclude from current research that

[1] In the text we use both the terms 'normal readers' and 'non-dyslexics' to refer to average or good readers / readers who do not have a reading impairment. The term 'dyslexics' refer to those who have a diagnosis of dyslexia.

dyslexia is not treated anymore as a qualitatively distinct disorder? To answer this question we are going to look at research on dyslexia, especially research on causes of dyslexia.

Research on dyslexia

In the last decades, a lot of research is done on finding possible causes for dyslexia. As a result, a large variety of theoretical accounts exist on causes and correlates of the reading disorder. These theoretical accounts include: *Impaired phonological awareness* (Torgesen, Wagner, Rashotte, 1994; Share & Stanovich, 1995; Snowling, 2000a), *impaired phonological memory* (Fletcher, Lyon, Fuchs, & Barnes 2007; Siegel, 2003), *impaired orthographic awareness* (Olson, Forsberg, Wise, & Rack, 1994; Vellutino, Scanlon, Tanzman, 1994), *visual-perceptual and visual memory deficits* (Lyon, Fletcher, & Barnes, 2002; Snowling, 2000a; Jones, Branigan & Kelly, 2008), *magnocellular deficits* (Stein & Walsh, 1997; Livingstone, Rosen, Drislane & Galaburda, 1991), *low-level auditory processing deficits* (Farmer & Klein, 1995; Tallal, Miller, Jenkins, & Merzenich, 1997), *rapid naming difficulties* (Vaessen, Gerretsen, and Blomert, 2009; Bowers & Wolf, 1993), *attention deficits* (Facoeti & Molteni, 2001; Buchholz & Davies, 2005; Valdois, Bosse & Tainturier, 2004), *deficits in motor control* (Ramus, Pidgeon & Frith, 2003; Savage, 2004), and *language-based deficits* (Vellutino, Fletcher, Snowling, & Scanlon, 2004). Apart from research into cognitive and motor deficits there are also lines of research that entertain *neurobiological factors* like brain structure, brain functions, and even genes (see Pennington, 2009; Fletcher, 2009; Vellutino et al., 2004), and *environmental factors* such as poverty, literacy-related activities, and reading instruction (Fletcher, 2009). This overview is not exhaustive, but the aim was to show the large number of factors that have been related to dyslexia.

The list of cognitive correlates shows nicely that these theoretical accounts are about <u>distinct</u> cognitive components underlying reading. This focus on finding the 'real' cause in a specific component in the brain implies that dyslexia is still viewed as a distinct disorder that is qualitatively different from (less) skilled reading. In other words, the idea still exists that there are distinct mental components underlying the reading performance of dyslexic readers and normal readers. This way of thinking in distinct cognitive components is also visible is some titles of articles: 'Visual Deficits…and their Contribution to Components of Reading' (Jones et al., 2008), and 'Is developmental dyslexia modality specific? .....' (Marinella, Angelelli, Filippo, & Zoccolotti, 2011).

However, the idea of distinct mental components underlying reading does not fit with the evidence that reading performance of dyslexic children and adults lies on a continuum with that of normal readers. Distinct mental components underlying reading would predict that two distinct modes of reading performance exist causing a bi-modal distribution of performance measures, but this is clearly not the case; it causes a continuum. Thus, on the one hand we actually know that reading performance from both dyslexics and non-dyslexics lies on a continuum, but on the other hand we still (though implicitly) look for distinct mental components underlying reading. Moreover, this focus on searching for the 'real' cause of dyslexia in distinct cognitive components has still not generated some final conclusion: The overview of current research on causes shows that there is still no consensus about which theoretical account is the 'best'. The question then arises whether it is fruitful to continue thinking of reading as components? Or, can we perhaps adopt a new approach to the study of dyslexia to 'solve' the stated contradiction in current research – an assumption that can initiate the fundamental theoretical revision Shaywitz referred to?

Component dominant dynamics

We propose to look at the assumption underlying the 'component-dominant-thinking' on causal factors of dyslexia first. After all, this assumption does not fit with the results of the continuum of reading performances. We argue that the appealing idea of distinct mental components that would result in a bi-modal distribution stems from a long unexamined assumption about how components interact in a cognitive system, namely *component dominant dynamics*.

The view on how components in a system interact that has long influenced research on cognition is the view of 'component dominant dynamics'. In a system with component dominant dynamics behavior can be described in terms of their separate components (Holden, Van Orden, & Turvey, 2009). In other words, system behavior is the result of a linear combination of cognitive components and processes (see Figure 1). This is actually what we do in regression analyses: We want to distinguish different factors that contribute to a specific behavior and we can combine the weights of all factors additively to result in the behavior. Another example is snooker: The behavior of one ball can be causally traced to other balls and the cue (influences on the trajectory are linear and additive).

Figure 1. *Additive components in a system with component dominant dynamics.*

The hypothesis about component dominant system dynamics is the core assumption of modular approaches to cognition (Van Orden, Holden, & Turvey, 2003). In other words, the view of component dominant dynamics is the assumption underlying the idea of a bi-modal distribution of reading performances. However, because there is no empirical evidence for such a bi-modal distribution, one would expect that the approach of component dominant dynamics is not the most appropriate way to look at the process of reading. Would there be a different way to look at the cognitive system of reading that is more in line with empirical findings about the distribution of reading performance?

Research on skilled readers: interaction dominant dynamics

Holden et al. (2009) and Holden (2002) found support for an alternative type of system dynamics that forms the basis of the process of reading, indicated by the shape of response time distributions of word-naming tasks and lexical decision tasks presented to skilled adult readers. This approach is called *interaction dominant dynamics*. Before explaining how they were able to reach their conclusions, we will first describe the concept of interaction dominant dynamics.

In a system with interaction dominant dynamics, behavior can only be described in terms of the interactions between the components. In this approach behavior is not reducible to separate components: The behavior of the whole is different from the sum of its parts (Van Orden, Kloos, & Wallot, 2009; Van Orden & Holden, 2002). In such a system it is not possible to distinguish distinct, encapsulated causal cognitive components from one another. An example of a system with interaction dominant dynamics is an ant hill. An ant hill emerges out of the local interactions of ants with each other and their environment. There is not one ant guiding this process: All components, processes, events, and their interactions are relevant. Interactions in this type of system may be nonlinear and multiplicative and across multiple (time-)scales (see Figure 2). To study such a complex system, the object of study is the interaction itself, not necessarily the details of interacting components (Van Orden et al., 2003).

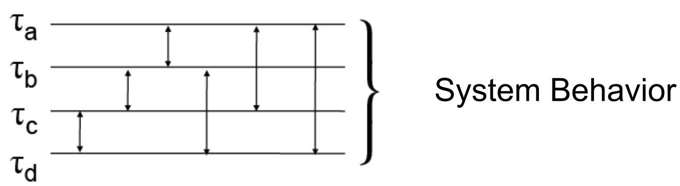

Figure 2. *Multiplicative interactions on multiple timescales.*

Traditionally, researchers study human behavior starting from the component dominant view. Humans are considered as machines by experimental psychologists and they view cognitive behaviors as caused by distinct 'modules' in the brain (Van Orden & Kloos, 2003). This is also the case in dyslexia: Different modules or modalities (for example auditory or visual modalities) are the subject of research projects. The idea that cognitive behaviors are caused by distinct modules in the brain is remarkable, because in biology, even the simplest animals are studied as complex systems with interaction dominant dynamics. Therefore, we think that the approach of interaction dominant dynamics may be more fruitful for the understanding of reading processes and dyslexia.

Reaction time distributions & types of interactions

As said, Holden et al. (2009) found evidence for interaction dominant dynamics underlying reading by looking at the shape of individual response time distributions of a word-naming task. But how are the shape of response time distributions and different types of dynamics in a system related to each other? In other words, how can the shape of a response time distribution supply information about how system's processes interact? To answer these questions we will first look at Gaussian distributions. Gaussian distributions support conclusions about how components interact, without knowing the identities or details of the interacting components (Holden et al., 2009). The Gaussian distribution originates from the central limit theory of Laplace, which shows the relation between additive interactions and dispersion of measurements. He reasoned that each measurement reflects the sum of many sources of deviation. The deduction was that the overall distribution of independent measurements would result in a bell-shaped distribution. This reasoning about a how system's components interact to produce a Gaussian curve was later empirically justified in ballistics research (Klein, 1997). From this type of research it was showed that a skilled target shooter's bullets form a familiar bell-shaped pattern around the bull's-eye, distributed as a Gaussian distribution. The dispersion around the bull's eye is the product of small accidental differences from shot to shot, that are the product of weak, independently acting factors. These weak and additive interactions ensure *component dominant dynamics* because the dynamics within components dominate interactions among components. Because there is evidence that independent and additively acting factors results in Gaussian distributions, it is licensed to infer that a distribution that appears as a Gaussian distribution comes from component dominant dynamics. The same inference has also been made with other types of distributions.

There are many processes, for example physical or biological, that rely on *multiplicative interactions* which produce lognormal distributions. The difference between additive and multiplicative interactions is that in a system with multiplicative interactions previous perturbations can be amplified or corrected, which can yield more skewed distributions or tighter distributions. In Figure 2B a lognormal distribution is depicted with the more skewed tail compared with the Gaussian distribution in Figure 2A. The name of the distribution stems from the fact that the distribution reappears as a Gaussian distribution if the axes of measurement undergo a logarithmic transformation. Lognormal distributions are produced by systems with relatively independent processes with multiplicative interactions (Holden et al., 2009).

Another type of distribution that is yielded by natural systems is an inverse power-law distribution. Inverse power-law distributions are produced by multiplicative *inter*dependent interactions. These distributions are much more skewed than lognormal distributions (see Figure 2C). Both lognormal and power-law distributions are produced by systems with *interaction dominant dynamics*. One of the differences is that a power-law distribution is more indicative of complex and less-skilled behavior. Applied to the field of reading, the assumption is that lognormal distributions (narrower, more stable distributions) come from more skilled readers, and that power-law distributions (shallower, unstable distributions) come from less-skilled readers (Van Orden, Moreno, & Holden, 2003).

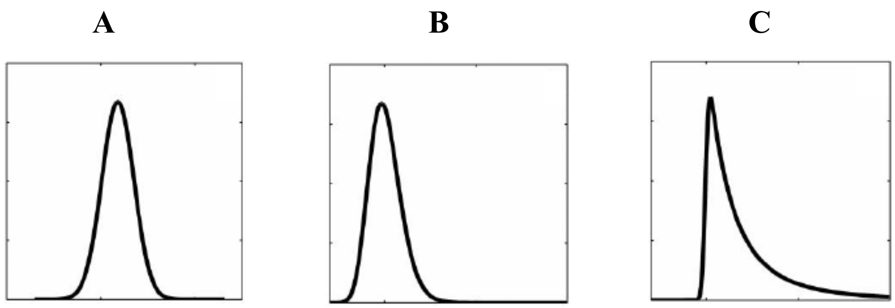

Figure 3. *Three different types of distributions.*
A = Gaussian distribution; B = lognormal distribution; C = inverse power-law distribution

The inference that an empirical distribution that appears as a Gaussian distribution stems from a system that produces weak and additive interactions, can also be made with the other types of distributions. That is, when lognormal or inverse power-law distributions mimic empirical distributions, then the empirical distribution originates in a vast array of multiplicative interactions, and thus stems from a system with *interaction dominant dynamics*. This is what Holden et al. (2009) showed: Participants' response time distributions from a word-naming task were successfully mimicked by mixtures of lognormal and inverse power-law distributions, thereby indicating that reading does not originate in component dominant dynamics, but in interaction dominant dynamics.

In short, whether a system behaves like component dominant dynamics (additive interactions) or interaction dominant dynamics (multiplicative interactions) is revealed by the type of response time distributions of a variable. In this study, we are going to use response time distributions to unravel dynamics underlying reading in children with and without dyslexia.

Goal of the study & hypotheses

In this study, we aim at gaining support for the assumption that the approach of interaction dominant dynamics – apart from the field of skilled reading – is also applicable to the field of impaired reading, that is, people with dyslexia. We hypothesize that the interdependence and multiplicative interactions between components during a reading activity (coming from interaction dominant dynamics) is even stronger in dyslexic children compared to non-dyslexics, because of all the cognitive correlates of dyslexia. Since inverse power-law distributions are indicative of this interdependent, complex and less-skilled behavior, we hypothesize that dyslexic children produce more power-law behavior than non-dyslexic children. We further assume that the non-dyslexic children will show more lognormal behavior, which indicates more skilled and less complex behavior. Because we are interested in the process of reading, we are going to look at response time distributions of dyslexic and normal readers presented with a *word-naming task*. These response time distributions will reveal the type of dynamics we are dealing with. We will study this by using a procedure developed by Holden, Van Orden, and Turvey (2011), in which response time distributions are simulated from mixtures of lognormal and inverse power-law distributions.

This study would be the first study that examines the interactive process underlying (impaired) reading which could explain the continuum in reading performances of dyslexics and non-dyslexics, thereby solving the contradiction that exists in the current field on research on dyslexia. Moreover, this is the first study that looks at type of distributions of word-naming tasks in a *clinical* population of non-dyslexic and dyslexic children. Knowing what type of dynamics we see in dyslexic as well as non-dyslexics will make us look differently at the nature of a learning disorder like dyslexia, which may have its implications for the search for causes, the way of diagnosing children with dyslexia, and the remediation of the disorder.

Method

Participants

Participants were 20 dyslexic children (13 boys, 7 girls) and 23 non-dyslexic children (8 boys, 15 girls), recruited from 6th grade of Dutch primary schools. Participants ranged in age from 11 to 13 (*M* age = 12.3 years). The dyslexic children all had an official diagnosis of dyslexia provided by an educational or child psychologist. To ensure that the reading skills of the recruited dyslexic children were substantially below the norm, and that the group of non-dyslexic children showed average or above average reading performances, we presented all participants with two widely used reading tests: The standardized word reading task 'Een-Minuut-Test' [One-Minute Test] by Brus and Voeten (1973) and the standardized pseudoword reading task 'Klepel' (van den Bos, Spelberg, Scheepstra & de Vries, 1994). For the selection criteria we used the scaled scores of the One-Minute Test and Klepel, with a mean of 10 and a standard deviation of three. The criteria were as follows: Scores of 6 or lower for the dyslexic children, and standard scores of 12 or higher for the non-dyslexic children. Informed consent was obtained via a passive parental consent procedure.

Materials and Procedure

The word-naming task consisted of 560 Dutch one-syllable words with a frequency per million > 0, selected from the CELEX database (Baayen, Piepenbrock, & van Rijn, 1993). Three different versions of the word-naming task were made by randomizing the word list. The versions were randomly assigned to the participants.

Participants were instructed to pronounce each word into a microphone as quickly and accurately as possible. Before the task started, participants completed 15 practice trials to become familiar with the procedure. In each trial, the participant was presented with one of the 560 target words, preceded by a fixation signal (+ + +), visible for 173 ms. After this fixation signal, a blank screen was visible for 200 ms, after which the target word appeared on the screen. The intertrial interval was 607 ms. All stimuli appeared in the center of a laptop screen, and remained on the screen for 10 seconds when no response was recorded. The words were presented in a sequential order, to make it possible to manually record wrong answers and erroneous reaction times (for example when the voice key recorded a sound before the stimulus word was read). The word-naming task required on average between 15 and 20 minutes.

Analyses

In order to reveal the dynamics underlying the reading skills of dyslexics and non-dyslexics, we looked at participants' response time distributions. We used the refined version of the Holden (2009) cocktail model (Holden, 2011). In this model, mixtures of lognormal and inverse power-law distributions are used to simulate individual participants' response time distributions. The main difference with the original description of the cocktail model is that the refined version is a parametric cocktail description rather than non-parametric. Moreover, the refined cocktail model is simpler and more compactly formulated. In order to test the generalizability of the refined cocktail model, Holden (2011) conducted analyses that indicated that the refined model successfully described empirical response time distributions. The first step in our analyses was creating probability density functions of each participants' response time distribution. Second, we approximated each distribution by using the refined description of the cocktail model, which we will explain in more detail in the second paragraph.

Probability Density Functions

Each participants' response time distribution for the word-naming task was plotted as a probability density function (PDF), which is a function that describes the relative likelihood for a response time to occur at a given point in time. The smooth and continuous probability density functions were obtained by using a standard procedure of Gaussian kernel density estimation (Silverman, 1989; Van Zandt, 2000). The maximum response time was set on 4000 ms. Before the PDF's were calculated, erroneous reaction times were removed from the dataset in order to make sure that only the valid response times were included in the density functions. Wrong answers or pronunciation errors were not excluded, because it is assumed that these errors are produced by the same dynamics that produce correct responses.

Simulation Methods and Parameters

To capture the shape of the empirical density functions, we used the refined cocktail model of Holden (2011). This model describes a weighted sum of two probability density functions: (1) A lognormal distribution of which its mean and standard deviation are treated as unknown free parameters and (2), an inverse power-law distribution which includes an onset threshold (a necessarily positive-valued lower bound of support for the distribution), and a scaling exponent as two unknown free parameters. The refined model is formulated such that it is a pure lognormal distribution for the values of the random variable below the power-law threshold (the 'front' or left side of the distribution). Above the threshold (the 'tail' or right side of the distribution), the refined cocktail is a mixture of a lognormal and an inverse power-law distribution with unknown weights. Because in the refined cocktail model the two probability functions (lognormal and inverse power-law) are mixed, three additional parameters have been created (proportion of the lognormal to the left of its mean (ρFLN); proportion of the lognormal to the right of its mean (ρBLN), and the proportion of power-law to the right of the lognormal mean (ρPL). Thus, the mixture of two PDF's in the formulation of the cocktail model resulted in seven different parameters. However, in order to ensure smoothness and unimodality of the distribution, constraints were enforced on the formulation of the cocktail model, which resulted in four free parameters (full derivation of the cocktail model can be found in the Appendix of Holden (2011).

The first two parameters are the mean and standard deviation of the lognormal distribution (Ω_{LN} and σ). The mean of the lognormal distribution Ω_{LN} basically indicates the location of most frequent reaction times, that is, the speed of the reaction times. When this value is relatively high, the overall reaction times are slower. The standard deviation σ controls the relative width of the distribution around Ω_{LN}, and tells something about the variability. A small standard deviation indicates a relatively small peak of the distribution, indicative of less variability. The third parameter is the scaling exponent of the inverse power-law distribution[2] (α), which is also indicative for the variability. A low value for α entails a more dramatic positive skew than a high value for α, which indicates mainly power-law behavior, and a higher value of α indicates more lognormal behavior. The fourth parameter is the relative weight of the lognormal in its mixture with the power-law tail (ρBLN). In our study, we have set the value for this parameter to zero. The parameters of the scaling exponent α and the proportion of lognormal in the tail ρBLN are not necessarily uniquely identifiable. Setting the ρBLN to zero forces all the variability to the scaling exponent α, which makes it easier to say something about differences in variability between the two groups. The implication is that we have only three parameters to report: the mean and standard deviation of the lognormal distribution (Ω_{LN} and σ), and the scaling exponent α. For a given reaction time dataset, the cocktail model parameters can be estimated with standard parameter estimation techniques, such as maximum-likelihood estimation or maximum spacing estimation. In this study we used the maximum-likelihood estimation technique. In short, the three parameters together can help us describe the shape of participants' distributions and reveal differences in shapes between the group of normal readers and dyslexic readers.

Goodness-of-fit

After the most optimal cocktail mixture was found, it was examined whether this mixture successfully mimicked the empirical distributions of word-naming times. This was done by using a two-sample Kolmogorov-Smirnov goodness-of-fit-test, with a Type I error rate of .05. In this test, the synthetic distribution from the cocktail mixture simulation was compared with the participants' probability density function to see whether the two distributions differed significantly from each other. The Kolmogorov-Smirnov test was passed when the p-value of the goodness-of-fit-test was above .05. All simulated distributions were plotted together with the density functions in separate figures for each participant. A simulation was considered successful when eyeballing revealed that the synthetic distribution captured prominent features of the participant's density function and if it passed the Kolmogorov-Smirnov test.

[2] Inverse power-law distributions are heavy tailed probability functions of the form $P(x) \sim ^{-\alpha}$, where typically $0 < \alpha < 3$ (Kello et al., 2010). Alpha (α) is the scaling exponent that describes the rate of linear decay in the slow tail of the distribution.

Results

From the 43 simulated distributions, 40 cocktail simulations successfully mimicked participants' response time distributions. Although the words from the target set of stimuli were all one-syllable words, and even for dyslexic children not extremely difficult, there were large differences in the characteristics of the response time distributions. In Figure 4, both the simulated distribution (white line) as well as the probability density function (black line) is depicted for three participants: One with a typical lognormal-dominant distribution, one with an intermediate distribution, and one with a power-law dominant distribution. We will first shortly discuss the characteristics of these three types of distributions[3].

Three types of distributions

Figure 4A shows the distribution from participant 25, a non-dyslexic participant. The distribution has a high peak and the tail is short, which indicates that fast response times are relatively common and slow response times are rare. The shape of this distribution can be characterized as a lognormal distribution. For this participant, the value for alpha is 11.97 (mean = 7.30), the value for the parameter Ω_{LN} is 6.22 (mean = 6.47), and the standard deviation σ is 0.11 (mean = 0.13). These parameters together create the lognormal shape of the distribution. The alpha is high, which is indicative for less complex and less variable, lognormal behavior. Also the small standard deviation, which results in a smaller width of the peak, is indicative of more stable behavior. The lognormal mean says something about the location: The response times are faster than on average.

Figure 4B depicts the distribution of a non-dyslexic participant (participant 27). This distribution has a somewhat lower peak than the distribution in 4A, and there are slower response times, resulting in a more skewed tail. This type of distribution comes from a mixture of lognormal and power-law distributions, called an 'intermediate mixture'. This is also visible in the different parameter values compared to participant 27. The value for alpha of this distribution is 7.19, the mean of the lognormal Ω_{LN} is 6.26, and the standard deviation is 0.12. The higher value for Ω_{LN} and standard deviation, and the lower value for alpha imply slower and more variable response times.

[3] This categorization is based on the categorization described in Holden et al. (2009). The parameters values of individual participants of our dataset were compared with parameters values of the three typical distributions described in the article of Holden et al. (2009).

Figure 4C illustrates a distribution from a dyslexic participant that can be classified as a power-law dominant distribution. The peak is much lower than the other two distributions, and the tail is heavily skewed. The response times are much slower on average, which is also visible in the relatively high value of Ω_{LN} of 6.70. The standard deviation is 0.23, which is caused by the large width of the distribution. The value alpha is 4.62, which is indicative of a power-law distribution generated by rather complex, and variable behavior.

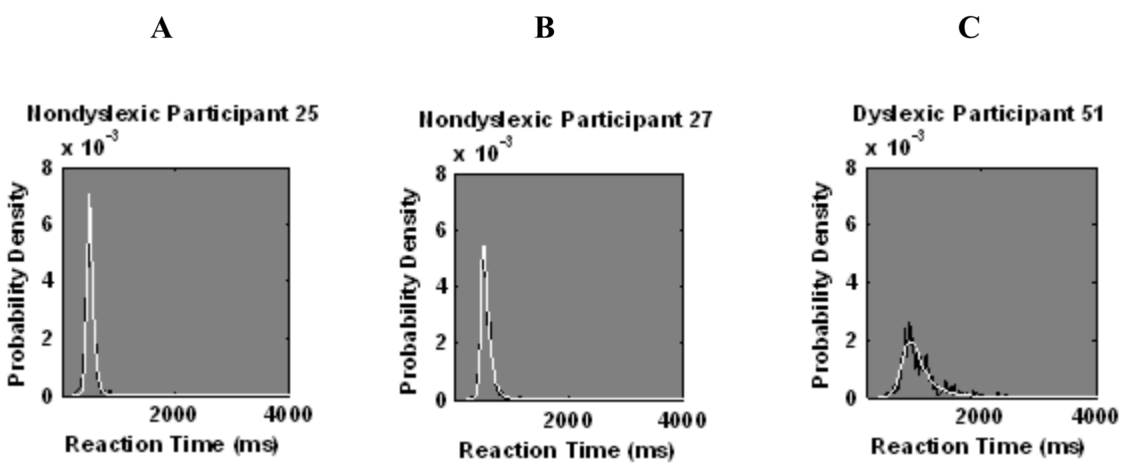

Figure 4 . *Probability density functions and cocktail simulations for three individual participants. The black lines represent the probability density functions of each participants' response time distribution. The white lines represent the simulated cocktail mixture of lognormal and inverse power-law distributions. Panel A resembles a typical lognormal dominant distribution, Panel C a typical power-law dominant distribution, and Panel B is a intermediate mixture from a lognormal and inverse power-law distributions.*

The previous paragraphs reveal that there are large differences in the shapes of the individual response time distributions, which can be categorized into three types of response time distributions. In general, a log-normal dominant distribution like Figure 4A is only seen for the non-dyslexics participants, and the power-law dominant distributions, as in Figure 4C, only for the dyslexic participants. Both non-dyslexics and dyslexics show intermediate mixtures like in Figure 1B. In Table 1 the parameter outcomes of all participants for which the simulated distribution successfully mimicked the participants' response time distribution are displayed. Three participants were discarded from the table. Before we discuss these results in further detail we shortly discuss the participants whose simulation failed.

Participants who did not show a good fit

One simulation (participant 43) did not pass the Kolmogorov-Smirnov test (p = 0.01). This means that the simulated cocktail mixture was not able to capture the shape of participants' response time distribution. In Figure 5A both the simulated distribution as well as the probability density function (PDF) of participant 43 is depicted. The reason why the simulation did not fit is probably because the tail of the simulated distribution is more slowly decaying than the tail of the PDF. The simulated distribution of participant 8 (Figure 5B) did pass the Kolmogorov-Smirnov test, but visual inspection of the distributions reveals that the simulation has no good fit with the PDF. In both cases, the parameters that were generated by the simulations did not provide reliable and valid values. Therefore it was decided to discard these participants from further analyses.

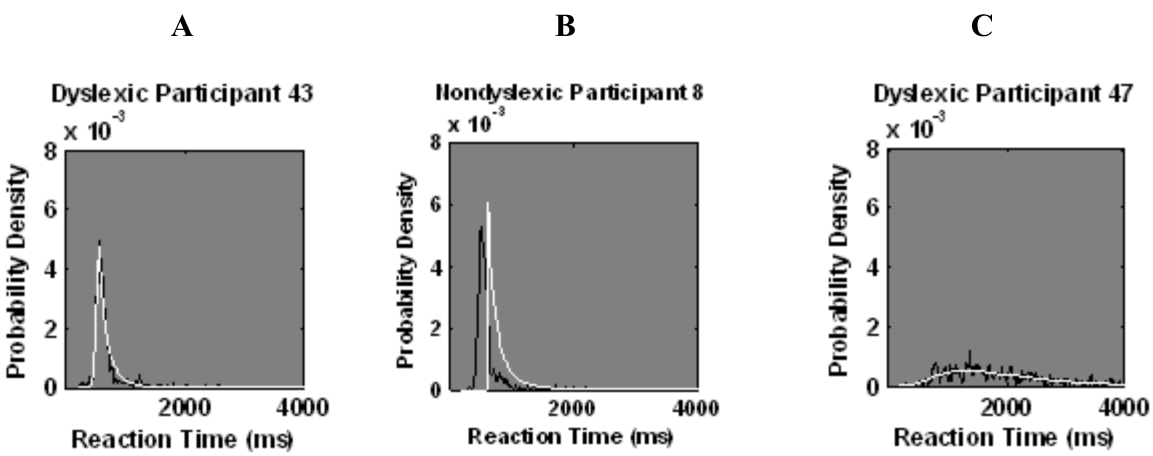

Figure 5. *Participants who did not pass the Kolmogorov-Smirnov test.*
The black lines represent the probability density functions of each participants' response time distribution. The white lines represent the simulated cocktail mixture of lognormal and inverse power-law distributions.

The third participant (5C) that was excluded from further analyses was participant 47. This (dyslexic) participant had a flat distribution, and this distribution cannot be classified as a mixture of lognormal and power-law distributions. Moreover, this participant displayed some extremes values on the parameters. Thus, also for this participant the values of the parameters are neither reliable nor valid and are therefore excluded from further analyses.

Overview of results of all participants

In Table 1 the values for all four parameters are shown. The participants are ordered by their value of alpha, with the highest alpha at the top. It becomes immediately visible that there is a clear split halfway the table, a split between the non-dyslexics and dyslexics (with the exception of participants 67, 22, and 16). The participants with good reading abilities have generally high or medium values of alpha, which is indicative of lognormal dominant or intermediate mixtures, and the participants with dyslexia have in general lower values for alpha, which shows that the reading abilities of dyslexics on the word-naming task comes from more complex behavior (power-law).

Table 1

Parameters Used to Generate Synthetic Distributions (Ordered by Alpha of Word-Naming Task)

Participant	Readers	α	Ω_{LN}	σ	*p*
25	normal	11.17	6.22	0.11	0.74
15	normal	11.14	6.08	0.05	0.28
32	normal	10.46	6.37	0.16	0.98
11	normal	10.23	6.31	0.13	0.86
28	normal	9.77	6.15	0.08	0.52
33	normal	9.54	6.20	0.10	0.81
31	normal	9.46	6.21	0.12	0.35
72	normal	9.29	6.18	0.09	0.67
5	normal	9.19	6.26	0.11	0.45
35	normal	9.16	6.50	0.17	0.22
37	normal	8.95	6.18	0.09	0.33
9	normal	8.81	6.28	0.12	0.71
26	normal	8.35	6.35	0.13	0.96
71	normal	8.34	6.17	0.10	0.15
23	normal	7.89	6.25	0.11	0.91
67	dyslexic	7.79	6.39	0.11	0.50
38	normal	7.77	6.18	0.09	0.24
2	normal	7.71	6.41	0.13	0.85
3	normal	7.51	6.36	0.15	0.95
1	normal	7.48	6.38	0.11	0.86
27	normal	7.19	6.26	0.12	0.98
52	dyslexic	6.93	6.38	0.16	0.37
13	dyslexic	6.51	6.51	0.16	0.93
69	dyslexic	6.48	6.34	0.13	0.60
70	dyslexic	6.43	6.44	0.15	0.80
58	dyslexic	6.40	6.43	0.14	0.24
36	dyslexic	6.33	6.33	0.13	0.42
61	dyslexic	6.08	6.44	0.12	0.07
29	dyslexic	6.02	6.25	0.12	0.67
34	dyslexic	5.90	6.55	0.20	0.12
22	normal	5.31	6.26	0.12	0.20
42	dyslexic	5.25	6.33	0.13	0.59
56	dyslexic	4.91	6.58	0.15	0.39
68	dyslexic	4.80	6.53	0.20	0.96
59	dyslexic	4.76	6.43	0.12	0.97
41	dyslexic	4.72	6.81	0.22	0.56
51	dyslexic	4.62	6.70	0.23	0.56
45	dyslexic	4.56	6.31	0.10	0.07
16	normal	4.53	6.32	0.13	0.95
53	dyslexic	4.48	6.47	0.11	0.08
M		7.30	6.35	0.13	

Note. α = alpha; Ω_{LN} = lognormal mean; σ = lognormal standard deviation; *p* = p-value of Kolmogorov-Smirnov test. Some participants have a high participant number. This is because recruited participants that did not meet the selection criteria also received a number.

In Figure 6, the differences in alpha become clear. The y-axis represents the alpha, and the x-axis represents the raw scores on the One-Minute Test. The vertical split is due to selecting criteria, but more important is the horizontal split, which makes nicely visible what the differences are.

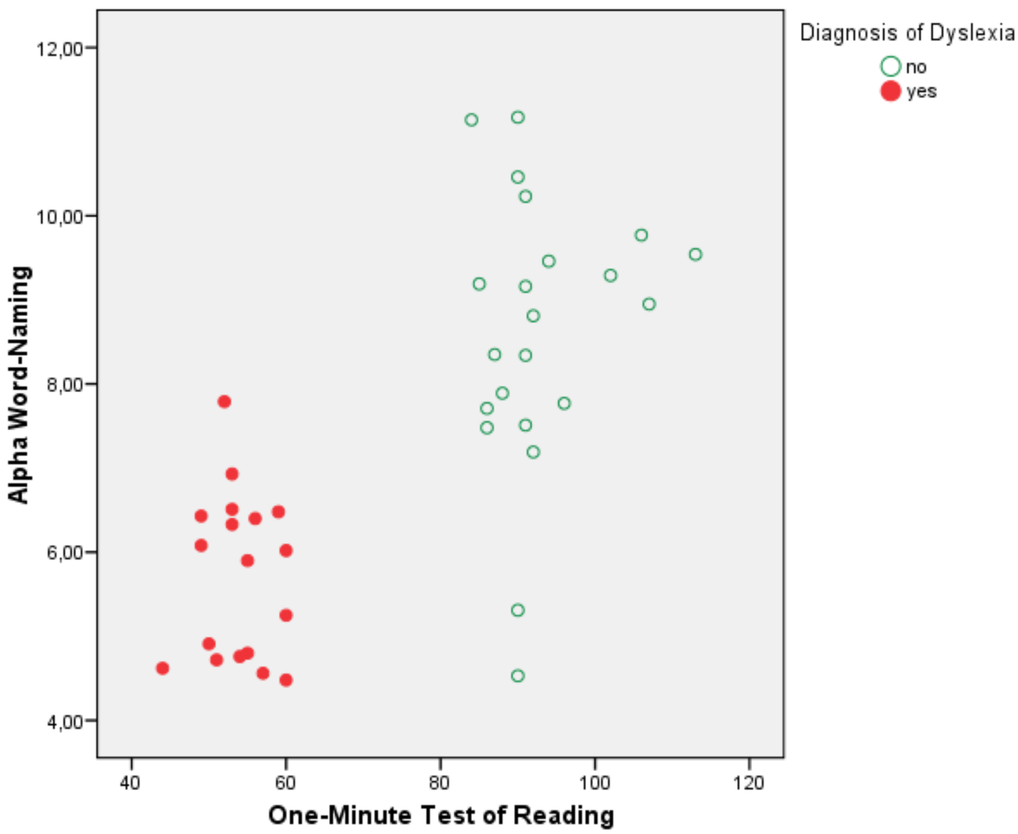

Figure 6. *Values of alpha on word-naming for dyslexics and non-dyslexics.*

Apart from the clear split between dyslexics and non-dyslexics it is also visible that all participants' values for alpha lie on a continuum. There is a gradual change from non-dyslexic participants with lognormal dominant distributions, to dyslexic children with power-law dominant distributions. In between there are both non-dyslexics and dyslexics with intermediate mixtures of lognormal and power-law behavior. The value of alpha is an important indicator for the type of distribution; however, the other parameters are also very informative and must be included in the analyses about differences in distributions. We have to view this in a holistic way: All parameters together make the shape of the distribution in a particular way.

To enhance the insight into the differences between dyslexics and non-dyslexics with respect to all parameters, we conducted an ANOVA (Analyses of Variance). In Table 2 the descriptive statistics are shown for the dyslexic group and the non-dyslexic group. The analysis revealed that there were significant differences between non-dyslexics and dyslexics with regard to all parameters. The values for alpha of the dyslexic group are significantly lower than the values for alpha of the group with normal readers. For the other two parameters - the mean of lognormal Ω_{LN} and standard deviation σ – the values of the dyslexics on these parameters are significantly higher. Because all these parameters, which together create the shape of a participants' distribution, are significantly different for the two groups, it provides evidence that dyslexic readers and normal readers show in general very different characteristics in their distributions. This is confirmed by the very large effect sizes (see Table 2).

Table 2

Parameters Statistics for Non-dyslexics and Dyslexics

	Parameters	Dyslexics (N=18)	Non-dyslexics (N=22)
α	*M*	5.72	8.60
	SD	0.98	1.65
	Confidence interval	5.23 – 6.21	7.87 – 9.34
	Cohen's *d*	2.12	
	ANOVA	F (1,38) = 42.40, $p < 0.01$	
Ω_{LN}	*M*	6.46	6.27
	SD	0.14	0.10
	Confidence interval	6.39 – 6.53	6.22 – 6.31
	Cohen's *d*	1.18	
	ANOVA	F (1,38) = 24.61, $p < 0.01$	
σ	*M*	0.15	0.11
	SD	0.04	0.03
	Confidence interval	0.11 – 0.13	0.13 – 0.17
	Cohen's *d*	1.63	
	ANOVA	F (1,38) = 10.74, $p < 0.01$	

In addition to the ANOVA we calculated the correlations between the two reading tests (One-Minute Test and Klepel) and the three parameters values α, Ω_{LN}, and σ (Table 3). With respect to the group of all participants, the correlations are all significant, indicating that there is a strong relationship between participants' scores on the reading tests and the shape of their distribution. For the groups of normal readers and dyslexic readers separately, this pattern is not that strong. The parameters must be viewed in a holistic way to be able to make a valid inference about the shape of the distribution. As a consequence, one significant correlation out of three does not give a lot of interpretable information. The weak correlations do indicate that the shapes of the distributions are relatively homogeneous within the distinct groups.

Table 3

Correlations Between Reading Tasks and Parameters Values

Group	Task	Parameters		
		α	Ω_{LN}	σ
All participants	EMT	0.72*	-0.70*	-0.54*
	Klepel	0.74*	-0.68*	-0.51*
Normal readers	EMT	0.16	-0.41	-0.30
	Klepel	0.17	-0.52*	-0.33
Dyslexic readers	EMT	-0.03	-0.60*	-0.51*
	Klepel	0.25	-0.29	-0.26

Note. * = $p < .01$

Discussion

The results of this study showed that the majority of empirical response time distributions of dyslexic readers and normal readers presented with a word-naming task were successfully mimicked by mixtures of lognormal and inverse power-law distributions, thereby supporting our hypothesis of interaction dominant dynamics that produce multiplicative interactions. Furthermore, the results indicated that, in general, the shape of the distributions of dyslexic children were different from that of the normal readers: The response time distributions of most dyslexic children can be classified as power-law dominant and the distributions of most non dyslexic children are lognormal dominant. This means that the process underlying reading performance of dyslexics is much more complex, variable, interdependent and less-skilled than the process underlying reading performance of normal readers, which produces more stable and skilled behavior. The differences in distributions became clearly visible by eye-balling the distributions, the significant differences between the two groups of readers with respect to all cocktail parameters that together produce a particular shape, and the strong correlations between the One-Minute Test and Klepel and the cocktail parameters. However, despite clear differences in shapes of distributions between dyslexics and no-dyslexics (on average) there is a gradual change from non-dyslexic participants with lognormal dominant distributions, to dyslexic children with power-law dominant distributions, with in between both non-dyslexics and dyslexics with intermediate mixtures of lognormal and power-law behavior. Even with these two groups with a large difference in reading performance, there is no clear line that separates the groups. In short, the results show that the view that interaction dominant dynamics is not only applicable to the field of skilled readers (e.g. Holden et al., 2009), but also to the field of impaired reading – dyslexia.

Theoretical implications

What do these results imply? First, we want to discuss some theoretical implications. As explained in the introduction, research on the causes for dyslexia focuses on a large variety of distinct modules or modalities in the brain – a focus that stems from the component dominant view. This study shows that there is an alternative way to look at (impaired) reading processes, the view of interaction dominant dynamics. From this view, behavior (i.e., reading performance) is not reducible to its specific components. Thus, we may have to stop finding the 'real cause' of dyslexia in one or more specific components, and instead focus on how the *interaction* between several components produces behavior, and how complex-system dynamics in impaired reading can be constrained to produce more stable behavior. Focusing on which component is going to win the battle of the 'real cause' is deemed to continue forever. After all, assuming interdependently interacting components in a system will always reveal components that are affected by an impairment in the system.

In addition, the results of the study can actually explain the continuum of reading performances in two ways. First, evidence that refutes the idea of distinct reading modes or distinct components underlying reading performance of dyslexics and normal readers indicate that it is difficult to classify dyslexia as a qualitatively distinct disorder. Second, the types of response time distributions of the two studied groups (very impaired readers and above average readers) are on a continuum: There was a gradual change from power-law dominant to log-normal dominant distributions. Both aspects shows us that the decision whether or not somebody has the reading disorder dyslexia is rather arbitrary. We cannot view dyslexia as an encapsulated impairment located somewhere in the brain, that is different from the group that 'just read somewhat slower'. This is an important implication to bear in mind during diagnostic activities. The diagnosis will thus remain arbitrary to some extent. Therefore, the goal of the assessment is not to find out whether the child really 'has' dyslexia or not, but to examine whether the reading performance is so impaired and resistant to intervention that it is legitimate to say that the problem behavior fits within our (arbitrary) definition of what dyslexia is.

Practical implications

In addition to theoretical implications on, for example, the search on the causes for dyslexia, the results of this study can also have implications for the remediation of the disorder. We found that dyslexics showed more variable and unstable distributions, and that the non-dyslexics showed more stable distributions. The reason why skilled readers generated more stable distributions is that they can rely on well-tuned internalized constraints. Constraints arise in relations among system's components, and they are narrowing down the degrees of freedom for change (Van Orden, Kloos & Wallot, 2009). So when there are well-tuned internalized constraints present in a system during reading, the constraints 'force' the system in the direction of for example a good pronunciation. But in impaired readers, there is a lack of constraints, so the system has more opportunities to produce 'wrong' behavior resulting in for example deficits in decoding words. Consequently, the goal of remediation must be to 'add' constraints to the system that reduces the chance to fall back into wrong responses. In this approach it is not relevant to look at the specific 'cause' of dyslexia in order to create an effective remediation program. It is more important to find out which constraints are present in the system of skilled readers that are lacking in the system of impaired readers. Research to interacting processes in the study of dyslexia would therefore be very relevant in this respect.

Research implications

Because of less well internalized constraints in the reading system in impaired readers, as well as the multiplicative interactions in the system, it is not strange that dyslexic children fall out of all kind of different tasks and modalities. We therefore argue that dyslexia cannot be that specific learning / reading disorder as some people pose it is. We think that a particular deficit in a system will spread out in the system through those multiplicative interactions. We therefore assume that dyslexic children also show power-law behavior in other (cognitive) tasks, apart from reading tasks. This would be an interesting venue for future research.

Another interesting option for future research is to investigate whether the shape of response time distributions from a word-naming task is related to children's response to intervention. Response to intervention could be a good indicator of the persistence of the reading problem, which in turn, is a good indicator for the decision whether or not the children could be classified as being dyslexic. The assumption would then be that children who are resistant to intervention show more power-law behavior and children who improve after intervention show a mixture of lognormal and power-law behavior. In this way, analyzing response time distributions could be helpful in the assessment of reading problems.

Conclusion

In sum, this is one of the first studies that generated support for the view that interaction dominant dynamics are the basis of skilled as well as impaired reading. Recently, Wijnants, Bosman, Cox, Hasselman and Van Orden (2011) also examined dyslexia from an interaction dominant dynamics perspective, using different methods of analyses, namely, complexity metrics. They concluded that dyslexia resides from dynamical instabilities in the coordination among components necessary to read, which could explain why dyslexic readers fall out on so many distinct tasks and modalities. The results of our study fit very well with this conclusion. We think that the approach of interaction dominant dynamics is a good alternative for the traditional approach of component dominant dynamics: The new approach appears to explain why *dyslexia appears as it does*.

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