Modeling Processing Speed in Developmental Language Disorder using Drift Diffusion Modeling

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Abstract

Children with Developmental Language Disorder (DLD) exhibit longer reaction times (RTs) than age-matched neurotypical children. Drift diffusion models estimate parameters influencing RT distributions: drift-rate represents speed of information accumulation, non-decision time represents other factors contributing to longer RTs, e.g., poor attention or motor coordination. Using a hierarchical Bayesian framework, we modeled RT data from visual search and mental rotation tasks completed by 3rd graders (N = 248). Children with impaired verbal abilities without accompanying nonverbal impairment (DLD) and those with global verbal/nonverbal impairments were compared to neurotypical children. Across tasks, children with DLD exhibited a lower drift rate than neurotypical children, indicating slower information accumulation, and no difference in non-decision time. Children with global impairments showed lower drift rates and higher non-decision times than neurotypical children. Results suggest directions for nuanced tests of the generalized slowing hypothesis of DLD. Clinical implications for diagnosis and treatment of DLD are discussed.

Keywords: Developmental Language Disorder, reaction time, drift diffusion modeling, processing speed, generalized slowing.

Introduction

Developmental Language Disorder (DLD) is a neurodevelopmental condition associated with clinically significant delays in language acquisition and affecting approximately 1 out of 14 children (Tomblin et al., 1997; Norbury et al., 2016). A growing consensus is that DLD is characterized by processing difficulties extending beyond language. According to the generalized slowing hypothesis (Kail, 1994; Leonard et al., 1983), individuals with DLD experience consistently slower information processing (longer reaction times [RTs]) across verbal and nonverbal domains than age-matched neurotypical individuals. In a meta-analysis synthesizing four decades of research on processing speed in DLD (Zapparrata et al., 2023), RT differences between DLD and neurotypical groups were moderate in size, (g = .47, CI = [.38; .55]). Effects were similar in magnitude across stimulus modalities (visual, auditory), stimulus types (linguistic, nonlinguistic), response modalities (verbal, button press), and tasks (simple RT, choice RT, interference control tasks).

However, RT differences alone are insufficient for determining the underlying processing difficulties that affect individuals with DLD. Because RTs are measured from stimulus onset to response onset, they reflect the time required to execute multiple cognitive processes, which vary by task. Moreover, RT distributions tend to be right skewed, meaning that any statistical test based on assumptions of normality is problematic, and both identifying and dealing with outliers is complex. Several statistical approaches have been put forward to handle extreme skew in RT data, such as analyzing median RTs, log transformations, and adopting more flexible linear modeling techniques (Lo & Andrews, 2015; Whalen, 2008). However, these techniques have statistical drawbacks of their own, and still lack the ability to decompose RTs into distinct components reflecting underlying cognitive processes.

From a decision making perspective, RTs can be decomposed into different component processes: stimulus encoding (i.e., perception and initial categorization), rate of information accumulation towards a decision-making criterion, and motor execution of the response. Drift diffusion modeling (DDM) is a computational framework for estimating specific components influencing decision making from a RT distribution (Ratcliff, 1978; Ratcliff & McKoon, 2008). DDM estimates four distinct parameters: The drift-rate parameter estimates the rate at which information is accumulated, and may be conceptualized as general cognitive ability or intelligence (Frischkorn & Schubert, 2018). The non-decision time parameter estimates other factors contributing to the response process, including stimulus encoding and motor execution time. The boundary separation parameter reflects the prioritization of speed over accuracy, which may be task dependent. Finally, the starting point parameter indicates an initial bias toward one of the two responses, e.g., tendency to respond same vs. different on a mental rotation task (Myers et al., 2022).

DDM has been used to elucidate how information processing changes over the lifespan (Ratcliff et al., 2010; 2012), and how it may differ in neurodevelopmental disorders, including attention deficit hyperactivity disorder (Huang-Pollock et al., 2017), autism (Pirrone et al., 2017) and dyslexia (Manning et al., 2022). Yet, despite wide interest in

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the generalized slowing hypothesis, this framework has yet to be applied to DLD. In the context of generalized slowing, drift rate and non-decision time are the main parameters of interest. Drift rate maps directly onto processing speed (Schubert & Frischkorn, 2020). Hence, we would expect it to be lower in individuals with DLD as compared to neurotypical peers (Kail, 1994; Zapparrata et al., 2023). Conversely, higher non-decision time indicates slower peripheral processing (e.g., stimulus encoding and motor coordination). Given evidence that individuals with DLD exhibit less efficient encoding of new words, potentially leading to poor quality representations (Gordon et al., 2021; McGregor et al., 2017), and also struggle with motor control and execution (Bishop & Edmundson, 1987; Hsu & Tseng, 2024), we might expected individuals with DLD to exhibit longer non-decision times than their neurotypical peers in addition to a lower drift rate.

Moreover, information processing difficulties are by no means specific to DLD, and extend to other neurodevelopmental disabilities. For example, children with intellectual disabilities have been found to have slower processing speed than neurotypical children and children with specific learning disorders (Cornoldi et al., 2014; Kaat et al., 2022). Impairments in stimulus encoding (Witt & Vinter, 2013) and motor skills are also evident in children with intellectual disabilities (Savage, 2007). Consequently, it remains unclear whether drift rate and non-decision parameters are differentially impacted in DLD relative to other clinical populations.

Research Objectives and Hypotheses

The current study represents an initial effort to apply DDM to RT distributions generated by children with DLD to elucidate underlying mechanisms. We secured a secondary dataset with two choice RT tasks (visual search, mental rotation) with data collected from a large sample of children in the 3rd grade. Based on standardized test scores, the children were categorized into three groups: neurotypical (i.e., verbal and nonverbal scores in the typical range), DLD (i.e., low verbal scores, typical nonverbal scores), and global impairment (i.e., low verbal and nonverbal scores). In accordance with the generalized slowing hypothesis, we expected to observed lower drift rates and higher non-decision times in language-impaired children (DLD and global impairment groups) as compared to neurotypical children, with larger magnitude of effects in the group with global impairments affecting verbal and nonverbal abilities.

Method

Participant Groups

The current study utilized secondary data from a sample of 248 3rd grade children (*M* = 8.99 years, *SD* = 0.36 years). Permission for the study was granted through a data use agreement with the University of Iowa. Note that a subset of the sample was included in previous reports (Miller et al., 2001; 2006). Using scores from a battery of norm-referenced tests of verbal and nonverbal abilities (Tomblin et al., 1996), we identified three groups of children. Neurotypical children (*n* = 135; *M* age = 8.97 years, *SD* = 0.36 years) scored in the typical range across verbal and nonverbal assessments; children with DLD (*n* = 66, *M* age = 9.02 years, *SD* = 0.35 years) had low scores on the verbal assessments and typical scores on the nonverbal assessments (DLD); children with global impairments (*n* = 47, *M* age = 9.02 years, *SD* = 0.34 years) had low scores on both verbal and nonverbal assessments. Additional children with typical scores on verbal assessments but low scores on nonverbal assessments were excluded.

Tasks

The children completed two choice RT tasks: visual search and mental rotation, with RTs and accuracy recorded on a trial-by-trial basis (Miller et al., 2001). Each task had 36 trials. The visual search task required participants to view a target figure, then scan an array of five nonsense figures from left to right; see Figure 1 for an example array. Children were instructed to strike one key if the target figure was present in the array of nonsense figures and to strike a different key if the figure was absent.

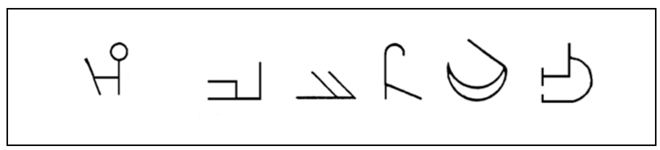

Figure 1: Sample stimulus item, Visual Search task

The mental rotation task presented a pair of figures, with the figure on the right rotated by 0, 60, or 120 degrees from the one on the left; see Figure 2 for sample images. Children were instructed to strike one key if the figures matched and another key if they were mirror images.

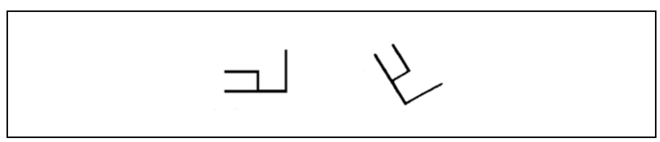

Figure 2: Sample stimulus item, Mental Rotation task

Data Cleaning

Data cleaning consisted of the removal of responses with negative reaction times (possibly indicating a premature button press prior to stimulus onset) and trials missing codes for accuracy (0 = incorrect, 1 = correct). Very low RT values (< 200 ms) were also removed from this analysis, as these reflect premature responses, i.e., too fast for full processing of the stimulus (Myers et al., 2022). For the visual search task, the final analytic sample comprised 247 children, with one missing participant in the DLD group. For the mental rotation task, the full sample of 248 children was included in the analysis. All data analysis code, fitted models, and preliminary analyses are located in an Open Science Framework repository (Johnson et al., 2025).

Figure 3 presents the RT distributions for the visual search task (upper panel) and the mental rotation task (lower panel). On the right of the vertical line at 0 are the RT distributions for correct responses for each participant group; on the left are the RT distributions for incorrect responses. The larger RT distributions on the right side of 0 indicate that the majority of children's responses were correct. Incorrect responses were especially rare on the visual search task, see Table 1 for mean RTs and accuracy for the two tasks. From the summary statistics of RT and accuracy, we can ascertain that visual search was a considerably easier task for children than mental rotation.

Table 1: Mean RTs (in seconds) and accuracy with associated standard deviations for visual search and mental rotation tasks.

Group	Visual Search		Mental Rotation	
	RT (*SD*)	*Accuracy* (*SD*)	*RT* (*SD*)	*Accuracy* (*SD*)
Neurotypical	1.89 (1.10)	97.1% (16.8%)	3.31 (2.29)	87.7% (32.9%)
DLD	2.10 (1.28)	97.5% (15.8%)	3.53 (2.55)	84.5% (36.2%)
Global Impairment	2.25 (1.28)	95.8% (20.0%)	4.12 (3.07)	73.9 % (43.9%)

Analysis Plan

DDM parameters tend to be correlated, due to their being decompositions of the same RT distribution. This can make it difficult to fit a DDM with only a small number of trials per participant (Myers et al., 2022). Hence, DDM can be hard to implement in studies involving children with developmental disabilities who cannot withstand lengthy testing sessions (Blackford, 2006). Multiple DDM approaches have been developed to facilitate parameter estimation including simplified EZ-diffusion models (Wagenmakers et al., 2007) and item response theory approaches (Tuerlinckx & Boeck, 2005). DDM has also been extended to accommodate a hierarchical structure, meaning that parameters are estimated at both participant and group levels (Vanderkerckhove et al., 2011). Hierarchical models were initially developed and are most easily implemented using Bayesian methods (Johnson et al., 2017). Given the dependencies within the present dataset (e.g., multiple trials per child), the present study adopted a hierarchical Bayesian approach using the HDDM library in Python (Wiecki et al., 2013).

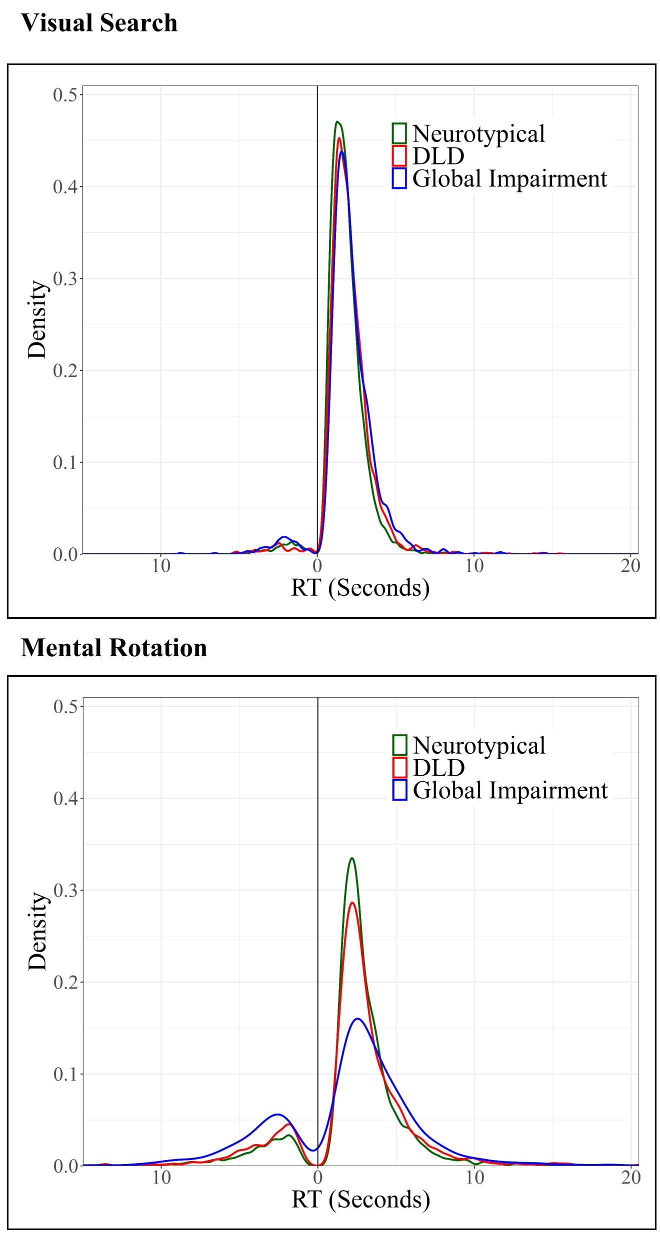

Figure 3: RT distributions for the visual search task (upper) and the mental rotation task (lower), with RTs to the left of the vertical line corresponding to incorrect trials and RTs to the right corresponding to correct trials.

Results

Preliminary Analyses

For a study of generalized slowing, the main parameters of interest are drift rate and non-decision time. However, as a preliminary step, we fit two models, one for each task, that estimated all four parameters by group. We then compared the full models to simpler models that only estimated the drift rate and non-decision time parameters at the group level and estimated boundary separation and starting point at the level of the overall sample. Comparing these models allowed us to confirm that boundary separation and starting point were negligibly affected; that is, the estimates of these parameters did not differ substantially between the two models, justifying our use of the simpler model; see Supplemental Materials for full reporting of our preliminary analyses (Johnson et al., 2025).

Visual Search

Table 2: Mean and 95% Crl Intervals for drift rate and non-decision time for the visual search task

Group	*Drift Rate*	*Non-decision Time*
Neurotypical	1.52 [1.45; 1.60]	0.14 [0.09; 0.20]
DLD	1.43 [1.33; 1.52]	0.18 [0.12; 0.25]
Global Impairment	1.30 [1.19; 1.41]	0.26 [0.18; 0.35]

Table 2 presents the mean drift rate and non-decision time parameters for the three groups estimated separately (drift rate; non-decision time, i.e., time to encode and respond). Figure 4 presents the posterior distributions for drift rate (upper panel) and non-decision time (lower panel), with parameters estimated separately for each group. We then assessed whether the estimates obtained for the two clinical groups (DLD, global impairment) differed significantly from the neurotypical group, and from each other. Using procedures outlined in the HDDM documentation (Wiecki et al., 2013), we derived significance values by computing the overlap between the posterior distributions for the neurotypical group and each of the clinical groups; see Table 3 for the results by parameter.

Table 3: P-values of statistical significance tests comparing drift rate and non-decision time on visual search.

Group	*Drift-rate*	*Non-decision Time*
Neurotypical vs. DLD	.033	.107
Neurotypical vs. Global Impairment	< .001	.002
DLD vs. Global Impairment	.054	.026

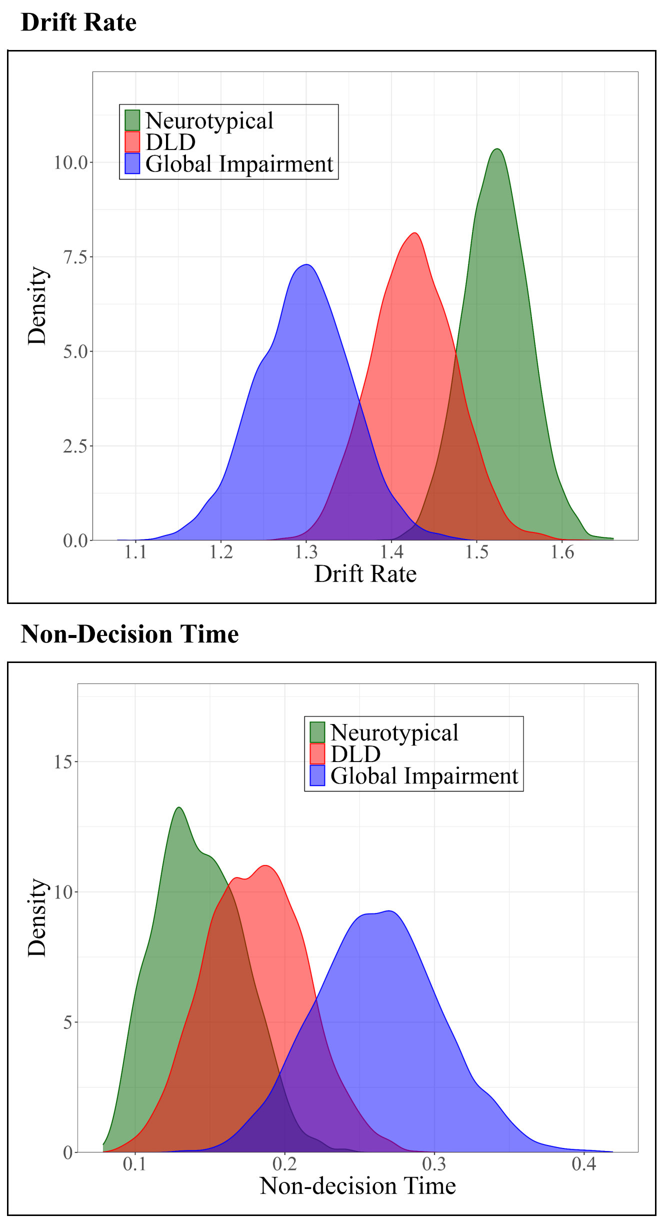

Figure 4: Posterior distributions of the drift rate (upper) non-decision time (lower) parameters for visual search.

Both the children with DLD and the group with global impairments exhibited a lower drift rate in comparison to the neurotypical group, indicating a lower rate of information accumulation. Drift rate was lower for the DLD group and group with global impairment. Drift rate was marginally slower in the group with global impairment than in the DLD group (p = .054), suggesting cumulative effects of verbal and nonverbal impairments on processing speed. For non-decision time, the group with global impairment exhibited higher non-decision time than both the neurotypical group and the DLD group, reflecting increased time for stimulus encoding and/or response execution. The correlation between estimated drift rate and non-decision time was statistically significant, but small in magnitude ($r(245) = .18$, $p = .003$) and unexpectedly positive.

Mental Rotation

Table 4: Mean and 95% CrI Intervals for drift rate (*d*) and non-decision time (*Ter*) for the mental rotation task

Group	*Drift Rate*	*Non-decision Time*
Neurotypical	0.87 [0.80; 0.93]	0.89 [0.83; 0.95]
DLD	0.72 [0.63; 0.81]	0.88 [0.80; 0.96]
Global Impairment	0.44 [0.34; 0.55]	1.01 [0.91; 1.11]

Table 4 presents estimated drift rate and non-decision time parameters for the mental rotation task, and Figure 5 displays the corresponding posterior distributions. As with verbal search, both of the clinical groups exhibited lower drift rates in comparison to the neurotypical group, and the group with global impairment had a lower drift rate than the group with DLD; see Table 5. For non-decision time, the group with global impairment exhibited higher non-decision time than both the neurotypical group and the DLD group, with the latter groups not differing from each other. Drift rate and non-decision time parameters showed a negative correlation of small magnitude ($r(246) = -.25$, $p < .001$).

Table 5: P-values of statistical significance tests comparing drift rate (*d*) and non-decision time (*Ter*) of each clinical group with the neurotypical group on mental rotation.

Group	*Drift Rate*	*Non-decision Time*
Neurotypical vs. DLD	.005	.596
Neurotypical vs. Global Impairment	< .001	.018
DLD vs. Global Impairment	< .001	.019

Discussion

RTs are one of the primary methods psychologists use to investigate psychological phenomena, and also one of the most difficult types of data to analyze and interpret (Draheim et al., 2019; Whelen, 2008). DDM conceptualizes RT tasks and resulting RT distributions from a decision- making perspective, allowing one to estimate contributions of different component processes (Ratcliff & McKoon, 2008; Schubert & Frischkorn, 2020). To provide a test of the generalized slowing hypothesis in DLD (Kail, 1994; Leonard et al., 1983), we leveraged DDM to estimate drift rate (speed of evidence accumulation) and non-decision time (speed of peripheral processing) across two choice RT tasks, comparing children with DLD to neurotypical children and with children to global impairments in verbal and nonverbal abilities. Using hierarchical DDM allowed us to fit models with a relatively small number of trials per participant. Non-hierarchical DDM approaches, by contrast, may require 10 times the number of RTs per participant for estimates to be stable (Myers et al., 2022).

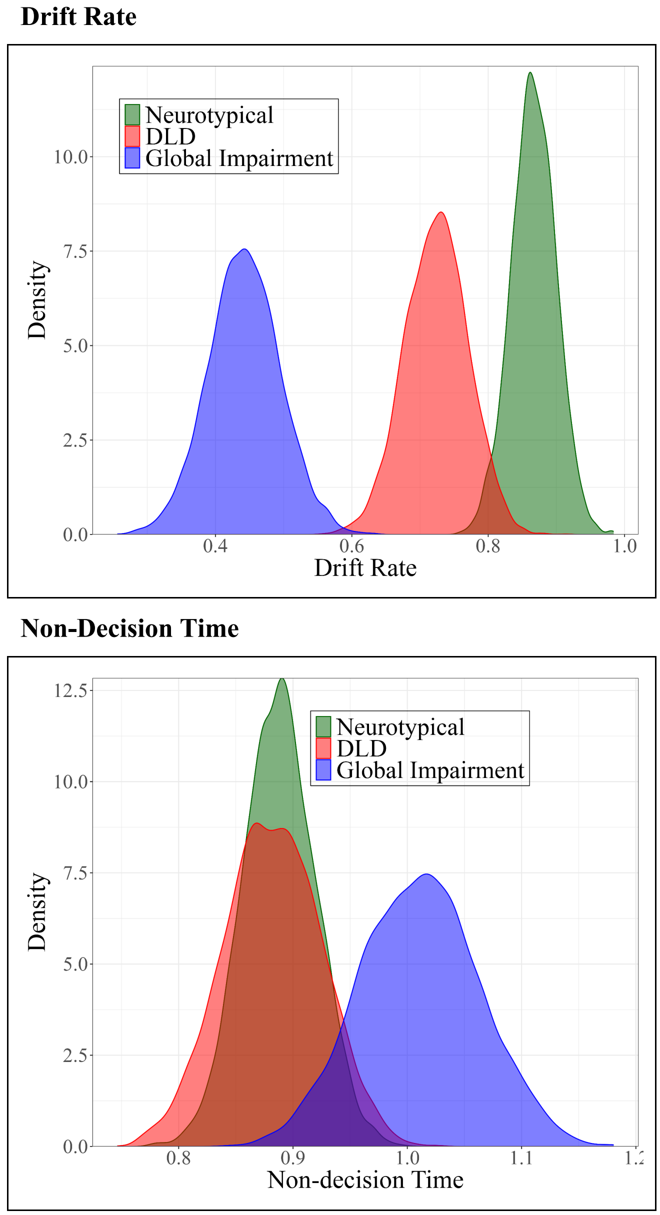

Figure 5: Posterior distributions of the drift rate (upper) non-decision time (lower) parameters for mental rotation.

In keeping with the generalized slowing hypothesis (Kail, 1994), children with DLD exhibited a lower drift rate than neurotypical children across two fully nonverbal choice-RT tasks (visual search, mental rotation), using nonsense objects as stimuli and button press responses. These findings further underscore how processing difficulties in DLD extend beyond language.

Unexpectedly, we found no evidence that non-decision time differed for children with DLD compared to their neurotypical peers on either task. In contrast, the group with global impairments showed increased non-decision times relative to the neurotypical and DLD groups across both tasks. This lack of a difference between DLD and neurotypical groups might suggest that processing difficulties in DLD affect centralized processing (rate of information accumulation), but not peripheral processing (stimulus encoding and response execution). Alternatively, it might reflect the nonverbal nature of visual search and mental rotation tasks. There is substantial evidence of auditory processing deficits in DLD, which affect encoding of spoken language (Corriveau et al., 2007). Thus, we might expect to see increased non-decision time for children with DLD on choice RT tasks, like auditory lexical decision, that depend on accurate and efficient encoding of spoken words (Edwards & Lahey, 1996; Jones & Brandt, 2018).

Similarly, there is compelling evidence of poor motor coordination and fine motor skills in children with DLD (Hill et al., 2001; Rechetnikov & Maitra, 2009). The motor requirements of both visual search and mental rotation tasks are minimal (e.g., button presses) as compared to the timed fine motor tasks (e.g., grooved pegboard task) that children with DLD find challenging (Bishop & Edmundson, 1997). Notably, the grooved pegboard and other time-based motor-skills tasks (e.g., bead-threading) do not yield trial-by-trial RT data and thus are not suitable for DDM. Choice-RT tasks, in contrast, tend to have minimal motor demands; hence, we might not expect to see increased non-decision time related to motor response execution.

In DDM, collinearity can be a problem between drift rate and non-decision time estimates, both of which reflect the same RT distribution. However, in our hierarchical DDM models, the observed correlations were very small (i.e., absolute values < .25), and were not consistent in directionality. For mental rotation, drift rate showed the expected negative correlation with non-decision time. That is, slower information accumulation coincided with longer stimulus encoding and/or response execution time. Unexpectedly, for the visual search task, we obtained a small positive correlation between the two parameters of interest, which may be spurious. Visual search proved to be a much easier task than mental rotation for the children, as indicated by smaller numbers of incorrect trials and higher estimated drift rates, reflecting a faster rate of information processing. Conversely, non-decision time was higher for mental rotation than visual search, which may reflect the increased time required for encoding the rotated figures.

Our findings that children with DLD showed a lower drift rate than neurotypical children across both tasks have implications for clinical diagnosis and treatment. Processing speed tasks show promise as diagnostic indicators of DLD that are not influenced by dialect differences or second language proficiency (Ebert, 2021; Park et al., 2020). Hence, use of choice-RT tasks may enhance efforts to diagnose DLD in children who come from diverse linguistic backgrounds. This is of importance given the lack of norm-referenced tests for the majority of human languages and dialects. Expanding the range of assessment tools may also help in diagnosing bilingual children with DLD since language impairment may manifest differently in bilinguals as compared to monolingual children (Kohnert, 2010).

Processing speed tasks are increasingly recognized as one of the diagnostic tools available to speech-language pathologists and other professionals, as indicated by the inclusion of one simple processing speed task in the NIH Toolbox (https://nihtoolbox.org/; Kaat et al., 2022). To the extent that population-based norms are available for specific processing speed tasks, nonlinguistic and nonverbal processing differences might serve as clinical markers for detecting DLD across diverse linguistic samples including bilingual speakers (Ebert & Pham, 2019; Park et al., 2020).

Zapparrata et al. (2023) restricted inclusion criteria for their meta-analysis to simple RT, choice RT, and baseline/congruent conditions of interference control tasks with minimal demands on executive functions (e.g., working memory) in an effort to isolate processing speed. However, our results suggest that simpler tasks may not be optimal for research on DDM because there may be too few incorrect trials. Simple tasks, while crucial for testing theories of the role of processing speed in language impairment, may not be ideal for diagnostic purposes. Tasks that tax the linguistic system in multiple ways often have greater diagnostic accuracy than more focused tasks (Park et al., 2015; Pawłowska, 2014). At the present time, not enough is known about the component processes of RT and their relations to neurodevelopmental disorders to establish the diagnostic accuracy of RT tasks. Studies such as the present one that use DDM or other modeling approaches are needed to make processing speed a useful clinical tool. Intervention studies might also serve as another fruitful source of data for understanding processing speed differences in DLD. Interventions can target specific processes within complex tasks, and their success can be evaluated through DDM. Those results will in turn inform the utility of RT tasks for diagnostic assessment.

In sum, our study represents an initial effort to apply DDM to elucidate processing differences associated with DLD and other neurodevelopmental disorders. Across nonverbal tasks, the finding of slower drift rates for children with DLD in comparison to neurotypical children aligns with the generalized slowing hypothesis. The finding that non-decision time was similar for DLD and neurotypical groups should be confirmed in future research with a greater variety of task demands. Despite having relatively few trials per participant, we were successful in fitting hierarchical Bayesian DDMs to available data from two nonverbal choice-RT tasks. Further research is needed to replicate findings with additional tasks and participant groups, including children growing up in multilingual environments and speaking languages other than English.

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