JNeurosci
THE JOURNAL OF NEUROSCIENCE

Research Articles | Behavioral/Cognitive

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https://doi.org/10.1523/JNEUROSCI.2385-24.2025

Received: 18 December 2024
Revised: 18 October 2025
Accepted: 9 December 2025

Latent neurocognitive mechanisms underlying quantity discrimination in children with and without mathematical learning disabilities

Abbreviated title: Latent neurocognitive mechanisms of math abilities

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Number of pages: 57

Number of figures: 5

Number of tables: 7

Number of words for abstract: 231

Number of words for introduction: 660

Number of words for discussion: 1499

Conflict of Interest Statement: The authors declare no competing financial interests.

Acknowledgement

This research was supported by grants from the National Institutes of Health (HD094623, HD059205, MH084164) and National Science Foundation (DRL-2024856) to V.M. and Stanford Maternal & Child Health Research Institute Postdoctoral Support Award to H.C. and P.M. We thank participating families and Miriam Rosenberg-Lee, Teresa Iuculano, Emma Adair, Shelby Karraker, and Samantha Mitsven for assistance with the study.

Abstract

Mathematical learning disabilities (MLD) affect up to 14% of school-age children, yet the underlying neurocognitive mechanisms remain elusive. We developed Drift Diffusion Model with Dynamic Performance Monitoring (DDM-DPM), an innovative cognitive model that captures both external and internal sources of structural variability in task performance. Combining DDM-DPM with functional brain imaging, we examined symbolic and non-symbolic quantity discrimination in female and male children with MLD and typically developing children matched on age, gender, and IQ. Children with MLD showed format-dependent alterations in response caution and post-error adjustment, despite similar observed performance measures between groups. The latent cognitive processes during symbolic quantity discrimination predicted broader mathematical abilities better than those during non-symbolic quantity discrimination. Neuroimaging results revealed that reduced activity in middle frontal gyrus mediated deficits in response caution in symbolic format, while reduced activity in the anterior cingulate cortex mediated deficits in post-error adjustment in symbolic format in children with MLD. These findings provide novel support for a multidimensional deficit view of MLD that extends beyond basic number processing to include metacognitive processes. Our findings also provide novel support for and extend the access deficit model, which posits that individuals with MLD may have relatively intact quantity representations but struggle with numerical representations in symbolic formats. Our study highlights the value of integrating latent cognitive modeling with neuroimaging to reveal subtle mechanisms underlying learning disabilities and identify potential targets for intervention.

Significance Statement

Considerable debate exists regarding the nature of deficits in mathematical learning disabilities (MLD). By developing an innovative computational model that captures subtle aspects of decision-making processes, we reveal that children with MLD show specific difficulties in adapting their problem-solving strategies when working with numerical symbols. Using brain imaging, we found that these difficulties are linked to reduced activity in brain regions involved in monitoring and adjusting behavior. Importantly, these deficits were specific to symbolic number processing and predicted children's broader mathematical abilities. Our findings suggest that MLD involves not only difficulties with basic number processing, but also problems in regulating cognitive strategies when working with numerical symbols. This insight could lead to more effective interventions for children struggling with mathematics.

Introduction

Mathematical proficiency is critical for professional success and independent living in our society (Parsons & Bynner, 2005). Mathematical learning disabilities (MLD) affect up to 14% of school-age children (Geary et al., 2012), posing a significant barrier to academic achievement and future employment (Butterworth, 2011). Despite its prevalence and impact, the cognitive mechanisms underlying MLD remain poorly understood partly due to limitations in conventional behavioral measures that may not capture distinct cognitive profiles. Here we introduce Drift Diffusion Model with Dynamic Performance Monitoring (DDM-DPM), an innovative cognitive model that integrates dynamic performance monitoring based on continuously adaptive metacognitive processes in a drift diffusion modeling framework. This approach enables the identification of latent cognitive processes that may not be apparent using traditional behavioral measures and provides insights into the nature of MLD.

The etiology of MLD has been a subject of considerable debate. The core deficit model posits that MLD is associated with impairments in fundamental number sense, affecting the ability to represent or process both non-symbolic (e.g., arrays of dots) and symbolic (e.g., Arabic numerals) quantities (Butterworth et al., 2011; Decarli et al., 2023; Piazza et al., 2010). In contrast, the access deficit model suggests that individuals with MLD have relatively intact non-symbolic representations of quantities but struggle specifically with accessing these representations when processing symbolic numbers (De Smedt & Gilmore, 2011; Rousselle & Noël, 2007). Despite extensive research, evidence supporting these accounts remain mixed, partly due to limitations in conventional behavioral measures used to test these hypotheses.

Complementing these domain-specific accounts, evidence suggests that deficits in executive function and metacognitive processes may be crucial for understanding MLD (Bull & Lee, 2014; Davidson et al., 1994; Desoete & DeWeerdt, 2013; Fias et al., 2013; Menon, 2016; Menon & Chang, 2021; Menon & Chang, 2022; Peters & De Smedt, 2018; Szucs et al., 2013). The ability to monitor performance, detect errors, and adjust behavior accordingly (Bellon et al., 2019; Bellon, Fias, & De Smedt, 2020; Bellon et al., 2021; Moser et al., 2011) is particularly critical in mathematics, where solutions to problems often require multiple procedures and verification of intermediate results (Cragg et al., 2017). Despite their importance, computational models that can dissociate these processes have been lacking, limiting our understanding of how alterations in cognitive control and metacognitive processes contribute to mathematical difficulties.

To address this limitation, we developed DDM-DPM by decomposing decision-making processes underlying math problem solving into distinct components (Ratcliff et al., 2016), including the quality of accumulated information (drift rate), speed-accuracy settings (response caution), and performance monitoring (post-error adjustment). A key advantage of DDM-DPM is its potential to reveal fine-grained individual differences in cognition that may not be apparent from observed measures. Our study employs an integrated approach to examine whether children with MLD, identified using standardized assessment of arithmetic (Woodcock et al., 2001), process quantity discrimination differently from typically developing children, even when achieving similar performance. Examining children with comparable performance allowed us to isolate latent cognitive mechanisms independent of confounding factors such as task difficulty, motivation, or general cognitive differences, addressing whether similar outcomes arise from fundamentally different cognitive processes. While previous neuroimaging studies have identified brain regions involved in numerical processing (Arsalidou et al., 2018; Menon & Chang, 2021; Menon & Chang, 2022), no previous work has systematically examined whether latent cognitive processes could explain underlying neurocognitive deficits in numerical processing in children with MLD.

We hypothesized that children with MLD would show alterations in latent behavioral measures of quantity discrimination, particularly in symbolic processing (De Smedt & Gilmore, 2011; Rousselle & Noël, 2007). We predicted that multiple latent behavioral measures would collectively predict standardized measures of math abilities. Additionally, we expected that individual differences in brain response in prefrontal and parietal cortical regions implicated in numerical cognition (Arsalidou & Taylor, 2011; Ashkenazi et al., 2012; Jolles et al., 2016; Rosenberg-Lee et al., 2015; Sokolowski et al., 2017; Yeo et al., 2017) would mediate the relationship between latent cognitive processes and the presence of MLD.

Materials and Methods

Participants

A total of 96 children in 2nd and 3rd grades (age: M = 8.19, SD = .63, 54 females) recruited with flyers sent to schools and posted at libraries and community centers in the San Francisco Bay Area participated in the study. All participants were right-handed and did not report any current neurological or psychiatric illness. Children with mathematical learning disabilities (MLD) were identified using *normed-based cutoff criteria* applied to math fluency, similar to previously published studies (Iuculano et al., 2015; Jolles et al., 2016; Rosenberg-Lee et al., 2015) and an important feature often considered a hallmark of MLD (Kaufmann et al., 2013). Children who scored at or below 90 (25th percentile or below) on the Math Fluency subtest of the Woodcock Johnson Third Edition (WJ-III) (Woodcock et al., 2001) were included in the MLD group (M = 84.75, SD = 5.73), and children who scored above 90 were included in the typically developing (TD) group (M = 104.80, SD = 9.58).

All study protocols were approved by the Stanford University School of Medicine Institutional Review broad and informed consent was obtained from the parents of the children. Children received $50 for completing MRI scanning session. Nine children were excluded from data analysis due to missing behavioral data (n = 4), below chance-level performance (n = 3), or technical issues from fMRI task (n = 2). Additionally, for brain imaging data analysis, 15 children were excluded due to poor image quality (n = 1), poor coregistration (n = 1), or excessive head movement (n = 13; see fMRI preprocessing in *Methods*) in the scanner.

For analysis of behavioral data, the sample included 87 children (34 children with MLD, 53 TD children; **Table 1**). For brain imaging analysis, the sample included 72 children (28 children with MLD, 44 TD children; **Table 2**). A total of 5 children with MLD were identified as extreme outliers within the MLD group (>3 IQR) for symbolic or non-symbolic response caution and were excluded from relevant behavioral (N = 5) and brain-behavioral analysis (N = 3). MLD and TD groups were matched on age, gender, and IQ in all analyses (ps > .160).

Experimental design and statistical analyses

We investigated how latent cognitive processes contribute to quantity discrimination abilities in children with and without MLD. The overall study design is summarized in **Figure 2**. Children completed functional MRI scanning session in which they performed on symbolic and non-symbolic number comparison tasks. Children determined which side of the screen had a larger quantity in symbolic (numeral) or non-symbolic (array of dots) format (see also *Symbolic and non-symbolic number comparison fMRI tasks*).

Trials with response times lower than 150ms were excluded from statistical analyses of behavioral data. For observed behavioral measures, we assessed numerical distance effects (DEs) for efficiency (by dividing accuracy by median response time for correct trials task to account for potential speed-accuracy trade-off; Townsend and Ashby (1978)), accuracy, and median reaction time for correct trials. Numerical DEs were assessed by subtracting behavioral measures on far distance trials from that on near distance trials to examine precision of quantity representation.

For latent behavioral measures, we applied Drift Diffusion Model with Dynamic Performance Monitoring (DDM-DPM) integrating psychometric and cognitive models within a Bayesian framework (Ratcliff et al., 2016; Ratcliff et al., 2015) to symbolic and non-symbolic quantity discrimination tasks to characterize latent behavioral dynamics of quantity discrimination in children with and without MLD. The distinct parameters derived from latent cognitive models can provide insights even when accuracy or reaction time measures reach ceiling or floor levels (Krajcsi & Kojouharova, 2017; Park & Starns, 2015; Ratcliff & McKoon, 2018; Ratcliff et al., 2015; Szardenings et al., 2018; Thompson et al., 2016). Importantly, DDM-DPM captured both internal and external sources of variability in task performance over time (see also **Figure 1** and *Latent cognitive modeling of quantity discrimination* section). DDM-DPM measured individual abilities separately for symbolic versus non-symbolic numerical stimuli and accounted for distance effects (near vs. far), allowing for differential functioning of items across groups (Dorans et al., 1992; Sireci & Rios, 2018).

Our latent behavioral measures of interest were numerical DEs of: (i) *drift rate* which indicates rate of information accumulation determined by representation of non-symbolic or symbolic quantity for Near vs. Far trials and (ii) *response caution* which indicates carefulness of judgments for Near vs. Far trials. The level of response caution determines the amount of information required before making a decision (Pedersen et al., 2017; van Maanen et al., 2011). Higher response caution indicates more conservative decision-making, where individuals require more information before responding, while lower response caution reflects less cautious responses. In addition, we examined (iii) *post-error adjustment* of response caution across error trials, which indicates shifts in degree of confidence required to respond after incorrect response. Post-error adjustment reflects how individuals adapt their decision-making strategy based on performance feedback. After making an error, individuals typically become more cautious in subsequent trials, requiring more information before making their next decision (Rabbitt, 1966). This adaptive behavior is crucial for learning from mistakes and optimizing performance (de Mooij et al., 2022; Jacobs et al., 2024).

Two-sample *t*-tests and Chi squared tests were performed for comparisons between groups of age, gender, or neuropsychological assessments. A mixed analysis of variance (ANOVA) with format (symbolic, non-symbolic) as a within-subject factor and group (MLD, TD) as a between-subject factor was conducted to assess format-dependent differences in number comparison task performance between groups. Follow-up two-sample and paired *t*-tests assessed group and format differences in quantity discrimination ability. Benjamini and Hochberg FDR correction was applied for *p* values associated with post-hoc tests. All the analyses, including estimates of effect sizes (Cohen's *d*, φ, η_p^2, ρ), were conducted in R (version 4.1.2).

For analysis including continuous measure of math ability, a composite measure of standardized scores of Wechsler Individual Achievement Test Third Edition (WIAT-III) (Wechsler, 2011) Addition and Subtraction subtests and WJ-III (Woodcock et al., 2001) Math Fluency, Calculation, and Applied Problems subtests was used (M = 99.7; SD =

10.1), which provided comprehensive, independent measures of mathematical achievement. Spearman correlations were used for analysis on relations between behavioral measures and brain-behavior relations to minimize influence of potential outliers. Multiple regression models were used to examine whether a set of observed or latent behavioral measures in symbolic or non-symbolic format could collectively predict individual differences in math ability. In addition, multiple regression analysis determined whether symbolic or non-symbolic measures together predicted math ability better than each measure alone.

In addition to frequentist statistics (e.g., *p*-values), Bayes factor (BF) was used to assess presence or absence of evidence for H_1 or H_o (Keysers et al., 2020). BF values greater than 3 provide evidence for H_1. BF values between .33 and 3 provide absence of evidence. BF values below .33 provide evidence of absence (evidence for H_o).

Details on statistical analyses of brain imaging data are described in *fMRI data analysis.* In addition, *Mediation of latent behavior-MLD status link* describes structural equation modeling applied to investigate the neurocognitive mechanisms by which latent cognitive processes could influence math achievement.

Rationale for assessment of quantity discrimination

Symbolic and non-symbolic quantity discrimination tasks were designed to assess children's basic numerical processing, independent from standardized arithmetic assessment used to identify MLD status. This approach represents a methodological strength for several reasons.

First, using a task independent from MLD classification criteria enabled us to examine whether children with arithmetic-based MLD process basic numerical information differently from TD children, even when achieving similar performance levels. This distinction between performance outcomes and underlying cognitive processes is fundamental to understanding learning disabilities: by controlling for overt performance differences, we were able to isolate and examine latent cognitive mechanisms independent of potential confounding factors such as task difficulty, motivation, or general cognitive differences. This approach enabled us to address a theoretically significant question about whether children with MLD rely on different cognitive processes to achieve similar outcomes on basic numerical tasks.

Second, this design allowed us to address the heterogeneous nature of MLD (Kaufmann et al., 2013; Szucs, 2016). Different MLD subtypes may show distinct patterns across mathematical domains, as some children may demonstrate preserved performance on simple numerical tasks while struggling with more complex mathematical operations. By examining quantity discrimination in children identified as having arithmetic difficulties, we were able to investigate whether preserved behavioral performance on basic numerical tasks reflects intact underlying cognitive processes or alterations in cognitive mechanisms that differ from typical development.

Third, the relative simplicity of the quantity discrimination task enabled a more precise dissociation of latent cognitive components (drift rate, response caution, post-error adjustment) of numerical processing. This level of mechanistic analysis would be challenging to achieve with more complex mathematical tasks, which would involve multiple interacting cognitive processes. The simplicity of the quantity discrimination task provided a methodological advantage for isolating specific cognitive mechanisms that may contribute to broader mathematical difficulties.

Symbolic and non-symbolic number comparison fMRI tasks

In the symbolic and non-symbolic number comparison fMRI tasks, two Arabic numerals (symbolic) or two sets of random arrays of dots (non-symbolic) were displayed horizontally. Stimuli were presented using E-Prime and displayed using an LCD projector and a back-projection screen in the scanner suite. In each trial, after a 500msec-fixation, a pair of symbolic or non-symbolic numerical magnitudes was presented for 1000msec, followed by a blank screen for 1500msec. Inter-trial intervals varied between 1700 and 3800msec. Participants responded which side had the larger quantity during the onset of the presentation of the magnitude pairs and before the end of the inter-trial interval. Participants were instructed to press a left button if the left side had a larger quantity and the right button otherwise. For the non-symbolic task, half of the trials controlled for the total area covered by each array of dots and the other half controlled for the average size of dots in each array to prevent participants relying on consistent perceptual features associated with number of items (Halberda et al., 2008).

We used numerical distance-based behavioral and neural measures of children's quantity discrimination ability. Since Moyer and Landauer's (1967) seminal work, numerical distance effects have been established as reliable measures of precision of numerical representation (Brannon & Merritt, 2011; Kaufmann et al., 2008; Moyer & Landauer, 1967; Nieder & Dehaene, 2009; Sasanguie et al., 2012). Using distance effects allowed us to examine brain responses associated with quantity discrimination while effectively controlling for low-level perceptual features, motor responses, and non-task-specific activity. This approach also enabled more direct comparisons between behavioral and neural measures, similar to a large body of neuroimaging studies (Ansari & Dhital, 2006; Bugden et al., 2012; Goffin et al., 2020; Kadosh et al., 2005; Kucian et al., 2011; Matejko et al., 2019; Sokolowski et al., 2019).

We used a 2 (Distance: near, far) × 2 (Magnitude: big, little) experimental design to control for effects of numerical magnitude at each level of numerical distance. Quantities between 1 and 9, excluding 5, were used in both tasks. Half of the trials had a near distance (1 unit) between the two quantities (e.g., 7:6), while the remaining trials had a far distance (5 units) between the two quantities (e.g., 3:8). Numerical magnitude was matched between the two distance conditions with an equal distribution of "big" (sum of pair of quantities greater than 10) and "little" (sum of pair of quantities less than 10) conditions. In each symbolic and non-symbolic comparison task, 16 unique pairs of quantities were presented 4 times, resulting in a total of 64 trials. Participants completed symbolic and non-symbolic tasks in two separate runs, with order of runs randomized across participants.

Latent cognitive modeling of quantity discrimination: DDM-DPM

The choice-coded reaction times, $Y_{i\,s\,t}$, where *i* denotes the individual, *s* denotes the format (symbolic vs non-symbolic), and *t* the specific trial, is distributed as per the Wiener distribution (Wabersich & Vandekerckhove, 2014), that characterizes the drift diffusion model (DDM). This distribution is characterized by response caution (or decision threshold) α, the non-decision time τ, the drift rate δ, and the initial bias β.

$$Y_{i\,s\,t} \sim DDM\ (\ \alpha_{i\,s\,t}\,, \tau_i, \delta_{i\,s\,t}\,, \beta_i\ )$$

In our model, the initial bias is fixed (0.5, no bias), and the non-decision time is a free parameter at the individual level.

However, the variability over time or trials in a task is not random, as is often assumed by standard choice and reaction time models. Such structural variability may depend on both internal and external sources of variation. Standard DDM typically incorporates discrete external sources of variability, such as inferring distinct parameter values for different experimental conditions. This is also incorporated into the DDM-DPM models where parameter values are differentiated based on near versus far distance, and symbolic versus non-symbolic stimuli. DDM-DPM (**Figure 1**) extends beyond identification of external sources of variability in task performance in the standard drift diffusion models in the following ways.

First, DDM-DPM accounts for internal sources of structural variability. This is accounted for in the trial-level response caution parameter (α), which is envisaged to vary dynamically from trial to trial based on a performance monitoring account. After correct trials ($\mathbb{I}$), the response caution is adjusted by a fixed percentage ($\epsilon_{i\,s}^{1}$) on each trial, accounting for the drift in response caution that may typically be seen over the course of a task as individuals become more familiar with the task and may be seen either as a form of learning or attentional modulation. After incorrect trials (1- $\mathbb{I}$), the response caution is adjusted by a different fixed percentage ($\varepsilon_{i\,s}^{0}$), reflecting post-error adjustments. These performance monitoring parameters are inferred separately for symbolic and non-symbolic stimuli.

$$\alpha_{i\,s\,t} = \alpha_{i\,s\,(t-1)} \left(1 + \epsilon_{i\,s}^{1}\mathbb{I}_{i\,(t-1)} + \varepsilon_{i\,s}^{0}\left(1 - \mathbb{I}_{i\,(t-1)}\right)\right)$$

Second, the drift rates (δ , which drives the efficiency of the choice process or is an indicator of the efficiency of information processing) at a trial level are inferred by combining individual (i), group (g), stimuli (s), distance (d), and item (k) level effects. The individual level drift component $\gamma_{i\,s\,d(t)}$ varies by modality of stimuli (symbolic vs non-symbolic) and distance (near vs far). This individual level drift component is modulated by item-level effects in a continuous item-response theoretic manner (Supekar et al., 2021). The item-level effects are inferred as latent item difficulties ($\eta_{s\,k(t)g(i)}$) that vary around a mean for each category (*s,* symbolic vs non-symbolic), by each sub-group (*g,* MLD vs TD), and are inferred based on item-level log-ratios (*k*). This allows for continuous differences in trial-level dynamics of the drift rate even within different categories of stimuli.

$$\delta_{ist} = \frac{\gamma_{i\,s\,d(t)}}{(1 + e^{-\eta_{s\,k(t)g(i)}})}$$

DDM-DPM incorporates hierarchical priors separately for MLD and TD groups and infers the parameters for both sets of stimuli – symbolic and non-symbolic – within the same overall model, to allow certain model parameters, such as non-decision times, to be held constant over both sets of stimuli. The parameters $(\gamma_{isd}\,, \eta_{skg}\,,\ \epsilon_{is}^{1}, \epsilon_{is}^{0}, \alpha_{is1}, \tau_i)$ are free parameters in the model. Together, the latent parameters derived from our cognitive models account for within-individual structural variability in task performance over time, between-individual differences, and group differences in item difficulty levels.

Parameter inference for DDM-DPM

DDM-DPM was implemented in a hierarchical Bayesian framework using JAGS (Plummer, 2003). Using MCMC sampling, we ran the model with 3 chains of 13000 samples each, with a burn-in of 10000. The model showed strong parameter recovery, with correlations between generated and recovered parameters ranging between 0.85 to 0.99.

fMRI data acquisition

Images were acquired on a 3T GE Signa scanner (General Electric, Milwaukee, WI) using a custom-built head coil at the Stanford University Lucas Center. Head movement was minimized during the scan by cushions placed around the participant's head. A total of 31 axial slices (4.0 mm thickness, 0.5 mm skip) parallel to the anterior commissure (AC)-posterior commissure (PC) line and covering the whole brain were imaged using a T2* weighted gradient echo spiral in-out pulse sequence (Glover & Lai,

1998) with the following parameters: TR = 2 sec, TE = 30 msec, flip angle = 80°, 1 interleave. The field of view was 22 cm, and the matrix size was 64 x 64, providing an in-plane spatial resolution of 3.4375 mm. The total length of the run was 6 minutes and 10 seconds. To reduce blurring and signal loss from field inhomogeneity, an automated high-order shimming method based on spiral acquisitions was used before acquiring functional MRI scans (Kim et al., 2002). High-resolution T1-weighted 3D MRI sequences were acquired to facilitate anatomical co-registration of fMRI maps, with the following parameters: I = 400ms, TR = 5.9ms; TE = minimum; flip angle = 11°; field of view = 240mm; matrix size = 256 × 192; 170 axial slices (1.0-mm thickness).

fMRI data preprocessing

Images were preprocessed and analyzed using SPM12 (Ashburner et al., 2020). The first five volumes of each time-series were discarded to allow for signal equilibration. A linear shim correction was applied separately for each slice during reconstruction (Glover & Lai, 1998). Images were realigned to the first scan to correct for motion and slice acquisition timing, co-registered to each individual's structural T1 images, spatially transformed to standard stereotaxic space (based on the Montreal Neurologic Institute coordinate system), resampled every 2 mm using sinc interpolation, and smoothed with a 6mm full-width half maximum Gaussian kernel to decrease spatial noise prior to statistical analysis. A bandpass filter (.008-.1 Hz) was applied to the smoothed data to remove high frequency artifacts.

Volumes with greater than 0.5 voxel scan-to-scan displacement along linear or rotational axes were de-weighted, as well as volumes with greater than 5% change in global signal. The proportion of volumes with scan-to-scan displacement higher than 0.5 voxel did not exceed 10% across tasks. Translational (*x*,*y*,*z*) and rotational (pitch, roll, yaw) movement in millimeters were calculated based on the SPM12 parameters for motion correction of the functional images of each subject. We excluded participants with mean scan-to-scan displacement greater than 0.5mm in either task.

fMRI data analysis

First-level statistical analysis. Task-related brain activation was assessed using the general linear model (GLM) implemented in SPM12. At the individual subject level, brain responses representing correct trials for each of 2 (Distance) x 2 (Magnitude) conditions (i.e., near/big, near/little, far/big, far/little) were modeled using boxcar functions convolved with a canonical hemodynamic response function and a temporal derivative to account for voxel-wise latency differences in hemodynamic response. An error regressor was also included in the model to account for the influence of incorrect trials. Additionally, six head movement parameters generated from the realignment procedure were included to control for the potential influences of head motion. Serial correlations were accounted for by modeling the fMRI time series as a first-degree autoregressive process. GLM was applied to the symbolic and the non-symbolic tasks separately. Voxel-wise contrast maps were generated for each participant for the symbolic and non-symbolic tasks (**Figure 2**).

Our experimental design included two within-subject factors Distance (near vs far) and Size (little vs big), forming four conditions (“near/big”, “far/big”, “near/little”, “far/little”), which were included in the GLM. As our contrast of interest was that “near” conditions elicit stronger or weaker brain activity than “far” conditions (i.e., neural DE), “big” and “little” conditions were collapsed in each distance condition. Thus, we defined two contrasts – [1 -1 1 -1] (near vs far) and [-1 1 -1 1] (far vs near) – based on the order of task conditions (“near/big”, “far/big”, “near/little”, “far/little”) in the GLM model. For the contrast [1 -1 1 -1], betas of “far/big” and “far/little” were added and then subtracted from the sum of “near/big” beta and “near/little” beta. Similarly, for the contrast [-1 1 -1 1], betas of “near/big” and “near/little” were added and then subtracted from the sum of “far/big” beta and “far/little” beta. These contrasts allowed us to examine neural DEs, which corresponded to behavioral measures of numerical DEs.

Second-level statistical analysis. A whole-brain two-sample *t*-test between MLD and TD groups for symbolic and non-symbolic quantity discrimination tasks identified brain regions that are differentially engaged during Near vs. Far distance condition (i.e., neural DE) between children with MLD and TD children for each format. All statistical maps were masked with a grey matter mask, and significant clusters were identified using a height threshold of $p < .001$, with whole-brain family-wise error rate correction at $p < .05$ (spatial extent of 30 voxels) based on Monte Carlo simulations. Follow-up region-of-interest (ROI)-based analyses were performed to visualize the results, ensure that the results were not driven by outliers, and confirm differences in brain measures between groups. ROIs were defined as 6 mm spheres centered at the peak of the coordinates of brain regions showing significant results from whole brain analysis.

Mediation of latent behavior-MLD status link

We used structural equation modeling to investigate the neurocognitive mechanisms by which latent cognitive processes could influence math achievement. Structural equation modeling was conducted using the Lavaan package (Version 0.6-12) in R (Version 4.1.2.). Specifically, models were constructed to investigate how brain activation (neural DE) of an ROI (or estimated latent variable across a set of ROIs) mediates the influence of a latent behavioral measure on the presence of MLD. Difference of beta values between Near and Far distance conditions from each ROI (or estimated latent variable across a set of ROIs) were used for brain measure, and path estimates were used to assess relations between variables. The indirect effect (mediation) was estimated as the product of the coefficients for paths between variables. Akaike information criterion (AIC) and Bayesian information criterion (BIC) were used to identify best-fitting models (**Table 7**).

Results

Quantity discrimination in children with MLD compared to controls

To assess children's symbolic and non-symbolic quantity discrimination ability, we first obtained numerical DEs (Near minus Far distance trials) based on observed behavioral measures: efficiency score (by dividing accuracy by median response time for correct trials), accuracy, and median response time for correct trials. For all these observed behavioral measures, children's numerical DE was greater for non-symbolic, compared to symbolic, quantity discrimination (*F*s > 13.86, *p*s < .001, η_p^2s > .13, Bayes Factors [*BF*s] > 100; **Table 3**; **Figure 3A**). The main effect of group (MLD, TD) and group by format (non-symbolic, symbolic) interaction were not significant for numerical DE of all observed behavioral measures (*p*s > .059, *BF*s < .65).

Additionally, we examined whether children with MLD and TD children achieved similar or different levels of overall accuracy on quantity discrimination tasks. Overall, both groups of children performed well on quantity discrimination in both formats (MLD: accuracy *M*s = .89-.91) and (TD: accuracy *M*s = .90-.94). A 2 (format: symbolic, non-symbolic) × 2 (group: MLD, TD) ANOVA showed a significant main effect of format ($F(1,83) = 24.75$, $p < .001$, $\eta_p^2 = .23$, *BF* > 100), but no significant main effect of group or interaction (*p*s > .07, *BF*s < 2.66), indicating that the two groups achieved similar levels of overall accuracy for these tasks.

These results indicate that observed behavioral measures were not significantly different between children with MLD and TD children in either symbolic or non-symbolic format.

Relation between quantity discrimination and math ability

To further assess individual differences in math ability on a continuum (i.e., independent of MLD status), we additionally examined a composite measure of standardized scores of Wechsler Individual Achievement Test Third Edition (WIAT-III) (Wechsler, 2011)

Addition and Subtraction subtests and WJ-III (Woodcock et al., 2001) Math Fluency, Calculation, and Applied Problems subtests.

We examined whether the continuous measure of math ability was associated with numerical DE of any observed behavioral measure. We found no significant relationship between the composite measure of math ability and numerical DE for observed behavioral measures ($|\rho|$s < .17, *p*s > .131, *BF*s < .56; **Figures 3B-C**). Additionally, we used multiple regression to examine whether observed behavioral measures in symbolic or non-symbolic format could collectively predict individual differences in math ability. Neither measures in symbolic nor non-symbolic format significantly predicted math ability (symbolic: adjusted $R^2 = .01$, $F(3,78) = 1.33$, $p = .271$, $BF = .15$; non-symbolic: adjusted $R^2 = -.002$, $F(3,78) = .96$, $p = .417$, $BF = .10$; **Figure 3D**).

These results indicate that children's symbolic and non-symbolic quantity discrimination ability assessed by observed behavioral measures did not significantly predict individual differences in math ability.

DDM-DPM derived latent cognitive measures in children with MLD compared to TD controls

To address our main question about whether there are similar or different behavioral dynamics between children with MLD and TD children for symbolic and non-symbolic quantity discrimination, we performed 2 (group: MLD, TD) x 2 (format: symbolic, non-symbolic) repeated measures ANOVA for 3 latent behavioral dynamic measures of interest: drift rate DE, response caution DE, and post-error adjustment. Results for each measure are described below.

Drift rate DE. We observed that the drift rate DE was more negative (lower drift rate for Near compared to Far distance trials) for non-symbolic, compared to symbolic, quantity discrimination (F (1,85) = 157.64, p < .001, $\eta_p{}^2$ = .65, BF > 100; **Table 4**; **Figure 4A**, first panel from the left). There was no significant group difference in the drift rate DE and interaction between group and format was not significant (ps > .112, BFs < .43). Additional analysis with the composite measure of math ability (see *Methods*) showed no significant relation between individual differences between math ability and symbolic or non-symbolic drift rate DE (ps > .074, BFs < .98; **Figures 4B-C**).

These results indicate that drift rate DE measures were not significantly different between children with MLD and TD children in either symbolic or non-symbolic format.

Response caution DE. Response caution DE was higher for symbolic, compared to non-symbolic, format (F (1,80) = 8.77, p = .004, $\eta_p{}^2$ = .10, BF = 13.86; **Table 4**; **Figure 4A**, second panel from the left) and for TD children, compared to children with MLD (F (1,80) = 13.39, p < .001, $\eta_p{}^2$ = .14, BF = 15.02). There was a significant interaction of group and format on response caution DE (F (1,80) = 6.57, p = .012, $\eta_p{}^2$ = .08, BF = 8.29), with a greater difference between groups for symbolic, compared to non-symbolic, format. Post-hoc paired t-tests showed that response caution DE was greater for symbolic, compared to non-symbolic, quantity discrimination in TD children (t(52) =

3.30, adjusted $p = .002$, $d = .45$, 95% CI [.17, .74], $BF = 16.84$) and not in children with MLD ($t(28) = -.59$, adjusted $p = .557$, $d = -.11$, 95% CI [-.48, .26], $BF = .23$). Two-sample *t*-tests showed that TD children showed greater response caution DE than children with MLD for symbolic ($t(80) = -3.26$, adjusted $p = .002$, $d = -.75$, 95% CI [-1.22, -.28], BF = 19.88) but not for non-symbolic ($t(80) = -1.57$, adjusted $p = .134$, $d = -.36$, 95% CI [-.82, .09], $BF = .69$) quantity discrimination task.

These results point to altered response caution DE during symbolic quantity discrimination in children with MLD.

Post-error adjustment. Post-error adjustment was significantly greater for symbolic, compared to non-symbolic, format (F (1,85) = 182.07, $p < .001$, $\eta_p^2 = .68$, $BF > 100$; **Table 4**; **Figure 4A**, third panel from the left) and no significant group difference was observed ($p = .11$, $BF = .32$). A group by format interaction was observed for post-error adjustment: TD children had greater post-error adjustment than children with MLD for symbolic format and children with MLD had greater post-error adjustment than TD children for non-symbolic format (F (1,85) = 36.92, $p < .001$, $\eta_p^2 = .30$, $BF > 100$). Post-hoc paired *t*-tests showed that post-error adjustment was greater for symbolic, compared to non-symbolic, quantity discrimination in both groups of children (MLD: $t(33) = 4.89$, adjusted $p < .001$, $d = .84$, 95% CI [.45, 1.24], $BF > 100$; TD: $t(52) = 12.71$, adjusted $p < .001$, $d = 1.75$, 95% CI [1.32, 2.19], $BF = 3.99$). Two-sample *t*-tests showed that TD children showed greater post-error adjustment than children with MLD for symbolic quantity discrimination task ($t(85) = -3.86$, adjusted $p < .001$, $d = -.85$, 95% CI

[-1.30, -.40], *BF* > 100). Children with MLD showed greater post-error adjustment than TD children for non-symbolic quantity discrimination task ($t(85) = 6.34$, adjusted $p < .001$, $d = 1.39$, 95% CI [.91, 1.87], *BF* > 100).

These findings indicate altered post-error adjustment during quantity discrimination in both symbolic and non-symbolic formats in children with MLD.

Relation between DDM-DPM derived latent cognitive processes and individual differences in math ability

Next, we conducted dimensional analyses to examine the relation between latent cognitive processes and individual differences in math ability. Response caution distance effects showed no significant correlations with math ability in either non-symbolic ($\rho = .16$, $p = .16$; *BF* = .67) or symbolic ($\rho = .21$, $p = .056$; *BF* = 2.79) formats (**Figures 4B-C**). In contrast, post-error adjustment showed significant correlations with math ability in both formats ($|\rho|$s > .27; *p*s < .009, *BF*s > 3.16; **Figures 4B-C**), indicating that mathematical performance was associated with adaptive adjustment following errors in quantity discrimination.

To assess the collective predictive ability of these latent cognitive measures, we then used multiple regression to examine whether latent behavioral measures in symbolic or non-symbolic formats could predict individual differences in math ability. We found that multiple latent measures (drift rate DE, response caution DE, and post-error adjustment) in both symbolic or non-symbolic format significantly predicted math ability (symbolic:

adjusted R^2 = .17, $F(3,78) = 6.39$, $p < .001$, $BF = 44.48$; non-symbolic: adjusted R^2 = .06, $F(3,78) = 2.86$, $p = .042$, $BF = .91$; **Figure 4D**).

To further address the potential contribution of latent measures in each numerical format to math ability, we conducted additional multiple regression analysis to determine whether symbolic and non-symbolic latent behavioral measures together predicted math ability better than each measure alone. Specifically, we examined whether the full model (Model 3) including all latent behavioral measures as predictors, compared with including either symbolic or non-symbolic latent behavioral measures alone (Models 1 and 2, respectively), better predict math ability (**Table 5**). Here, we found that the full model (Model 3) explained most variance in math ability (adjusted R^2 = .20, $F(6,75) = 4.32$, $p < .001$, $BF = 25.48$), significantly better than the model including non-symbolic latent behavioral measures alone (Model 2; $\Delta R^2 = .16$, $p = 0.002$, $BF = 28.06$). Critically, there was insufficient evidence ($.33 < BF < 3$) that the full model including both symbolic and non-symbolic latent behavioral measures (Model 3) explain additional variance in math ability, compared with the model including symbolic latent behavioral measures alone (Model 1; $\Delta R^2 = .06$, $p = .122$, $BF = .57$). Thus, we did not observe evidence that non-symbolic latent behavioral measures jointly predict math ability over and above symbolic latent behavioral measures.

These results indicate that latent behavioral measures of symbolic and non-symbolic quantity discrimination can collectively predict individual differences in math ability, with a greater contribution of symbolic, compared to non-symbolic, latent behavioral measures.

Neurocognitive mechanisms underlying the relation between latent cognitive processes and MLD

Next, we investigated the neurocognitive mechanisms by which latent cognitive processes could relate to children's MLD status (i.e., the presence of MLD). Among latent behavioral measures, symbolic response caution DE and symbolic and non-symbolic post-error adjustment were significantly different between children with MLD and TD children (adjusted *p*s < .002, *BF*s > 19.87; **Figure 4A**). For each of these latent behavioral measures, we used structural equation modeling (SEM) to test the hypothesis that the relationship between a latent behavioral measure and MLD status would be mediated by brain responses.

To address which brain regions could relate to children's MLD status, we examined brain regions in which children with MLD engaged differently from TD children during symbolic or non-symbolic quantity discrimination. A whole-brain analysis of group difference revealed greater neural DE in TD children, compared to children with MLD, in the left anterior cingulate cortex (ACC), bilateral middle frontal gyrus (MFG), right inferior frontal gyrus (IFG), and right superior temporal gyrus (STG) during symbolic quantity discrimination (**Figure 5A**; **Table 6**). No group difference was observed for neural DE during non-symbolic quantity discrimination. These results suggest format-dependent differences in the neural DE in frontal-cingulate and temporal brain regions varying as a function of MLD status.

The regions of interest included in SEM models were the brain regions identified from whole-brain analysis of symbolic quantity discrimination task for the latent behavioral measure included in the model. Specifically, the neural DE in the left ACC, bilateral MFG, right IFG, and right STG were included in the model that examined the relation between a symbolic latent behavioral measure (symbolic response caution DE or symbolic post-error adjustment) and MLD status. Results from these models are described below.

Symbolic response caution DE. Among the models examined for symbolic response caution DE, the indirect effect of neural DE in the right MFG (peak MNI coordinates [*x*, *y*, *z*]: [40 44 2]) in the relation between symbolic response caution DE and MLD status was significant ($z = -2.53$, $p = .011$; **Table 7**; **Figure 5B**). Specifically, symbolic response caution DE had a direct positive effect on the right MFG during symbolic quantity discrimination ($z = 3.87$, $p < .001$), which had a direct negative effect on MLD status ($z = -3.01$, $p = .003$).

No significant mediation was observed for the neural DE of the left ACC, left MFG, right IFG, or right STG in the relation between symbolic response caution DE and MLD status (indirect effects of the right IFG and right STG: ps > .075; **Table 7**). In addition to testing individual regions of interest, we also assessed the mediation effect of a latent variable estimated across all five regions of interest (ROI; left ACC, bilateral MFG, right IFG, and right STG). The model including this latent variable as the mediator between symbolic response caution DE and MLD status was not significant (indirect effect of the latent variable estimated from the five ROIs: $p = .068$; **Table 7**). The lack of significant mediation by other frontal and temporal cortical brain regions, despite their reduced neural distance effects in MLD, suggests a specific functional role of the MFG in mediating the link between careful responses during symbolic quantity discrimination and math ability.

Finally, we explored whether the brain regions identified from symbolic quantity discrimination (the left ACC, bilateral MFG, right IFG, or right STG) could mediate the relation between non-symbolic response caution DE and MLD status. This analysis showed no significant indirect effects of individual regions of interest (ps > .195), indicating that the findings were specific to the symbolic format.

Together, these findings suggest that low levels of neural DE in the right MFG region explain the mechanism underlying reduced response caution DE during symbolic quantity discrimination in children with MLD.

Symbolic post-error adjustment. Among the models examined for symbolic post-error adjustment, we found that the model including the left ACC (peak MNI coordinates [*x*, *y*, *z*]: [-2 32 12]) as the mediator between symbolic post-error adjustment and MLD status was significant (**Table 7**; **Figure 5C**). Specifically, symbolic post-error adjustment had a direct positive effect on the neural DE of the left ACC during symbolic quantity discrimination ($z = 2.51$, $p = .012$), which had a direct negative effect on MLD status ($z = -3.31$, $p = .001$). A significant indirect effect was observed for the left ACC neural DE in the relation between symbolic post-error adjustment and MLD status ($z = -2.05$, $p = .040$). The indirect effect of neural DE in the right MFG in the relation between symbolic post-error adjustment and MLD status was also significant ($p = .041$; **Table 7**). Based on AIC and BIC estimates (left ACC: 260.65 - 272.04; right MFG: 265.63 - 277.02), the mediation model including the left ACC was the best-fit model among the models with significant indirect effects.

In contrast to the findings of the left ACC or right MFG, no significant mediation was observed for the neural DE of the left MFG, right IFG, or right STG in the relation between symbolic post-error adjustment and MLD status (indirect effects of the left MFG, right IFG, and right STG: ps > .112; **Table 7**). In addition, the model including the latent variable (estimated across the left ACC, bilateral MFG, right IFG, or right STG) as the mediator showed no significant mediation effect (indirect effect of the latent variable estimated from the five ROIs: $p = .117$; **Table 7**).

Finally, we explored whether the brain regions identified to show significant group difference during symbolic quantity discrimination could mediate the relation between non-symbolic post-error adjustment and MLD status. This analysis showed no significant indirect effects of the left ACC, bilateral MFG, or right IFG (ps > .153). One exception was the right STG, which had a significant indirect effect in the relation between non-symbolic post-error adjustment and MLD status (z = 1.99, p = .047). Here, non-symbolic post-error adjustment had a direct negative effect on the neural DE of the right STG during symbolic quantity discrimination (z = -2.31, p = .021), which had a direct negative effect on MLD status (z = -2.99, p = .003). This unexpected finding indicates that reduced modulation of the right STG between numerical quantities may be one mechanism underlying atypically high levels of non-symbolic post-error adjustment in children with MLD. Similar to this observation, the superior temporal gyrus is thought be involved in processing and integration of multiple modalities (Beauchamp et al., 2004; Calvert, 2001) and altered brain responses in superior temporal gyrus have been observed during arithmetic task performance in children with MLD (Ashkenazi et al., 2012; Chen et al., 2021).

Together, these findings suggest that low levels of neural DE in the ACC explain the mechanism underlying reduced post-error adjustment during symbolic quantity discrimination in children with MLD.

Discussion

Our study provides novel insights into the cognitive mechanisms underlying mathematical learning disabilities (MLD). DDM-DPM extended conventional drift diffusion models by incorporating structural sources of within-individual variability (De Ribaupierre & Lecerf, 2018) and improving inferences about underlying neurocognitive mechanisms (Gluth & Rieskamp, 2017; Mistry et al., 2024). Critically, we isolated latent cognitive mechanisms independent of confounding factors such as task difficulty or general cognitive differences. These latent cognitive measures predicted children's mathematical abilities better than observed behavioral measures, with effects specific to symbolic quantity processing. Our neuroimaging results revealed that reduced neural activity in middle frontal gyrus (MFG) and anterior cingulate cortex (ACC) mediated altered latent cognitive processes in MLD.

Our findings support a multidimensional view of MLD encompassing basic numerical processing and higher order cognitive processes during quantity discrimination. To the best of our knowledge, our study is the first to demonstrate distinct latent-model-derived cognitive profiles between matched samples of children with MLD and typically developing (TD) children. Our computational modeling approach, combined with neuroimaging, paves the way for more refined diagnostic tools and targeted interventions for learning disabilities.

Latent behavioral dynamics reveals response caution and post-error adjustment deficits in MLD

Our analysis revealed reduced distance effects in response caution in children with MLD compared to TD children during symbolic quantity discrimination. In typical development, response caution naturally adapts to task difficulty. Consistent with this view, we found that TD children were more cautious when comparing close numerical quantities (e.g., 7 vs. 8) and less cautious when comparing distant numerical quantities (e.g., 2 vs. 7). However, children with MLD showed weaker modulation of this response caution based on numerical distance, specifically when processing symbolic numbers.

Importantly, these differences in response caution modulation were detected even though there were no differences in distance effects of observed accuracy or reaction time between groups, highlighting the sensitivity of DDM-DPM in detecting subtle differences (Ratcliff & McKoon, 2018; Szardenings et al., 2018). The ability to adaptively adjust decision-making strategies based on task demands is crucial for efficient mathematical problem solving and is particularly relevant for understanding the cognitive mechanisms underlying MLD.

In addition to response caution deficits, children with MLD showed reduced post-error adjustment during symbolic quantity discrimination. Interestingly, during non-symbolic quantity discrimination, these same children showed enhanced post-error adjustment, demonstrating heightened sensitivity to errors when comparing dot arrays. This dissociation across formats suggests that error monitoring mechanisms in MLD are not universally impaired but rather task-context dependent and provides more compelling evidence for the access deficit hypothesis rather than the core deficit model. The preserved or even enhanced error monitoring in non-symbolic quantity discrimination, coupled with specific deficits in symbolic format, suggests that children with MLD may have intact representations of quantity but struggle specifically with accessing and manipulating these representations when working with abstract symbols.

Latent cognitive processes predict broader mathematical abilities

We examined whether latent behavioral measures relate to mathematical abilities assessed by standardized math assessments. Multiple latent behavioral measures derived from DDM-DPM predicted math ability, with stronger effects for symbolic compared to non-symbolic tasks. Importantly, while symbolic and non-symbolic measures together predicted math ability better than non-symbolic measures alone, non-symbolic measures did not predict math ability beyond symbolic measures. This unique predictive role of latent mechanisms of symbolic number processing in math achievement suggests that deficits in adaptively adjusting decision-making strategies and learning from errors during judgements of symbolic number magnitude may contribute to broader difficulties in mathematical problem-solving, where flexible strategy adjustment is often required (Bull & Lee, 2014; Cragg et al., 2017).

Middle frontal gyrus mediates response caution deficits in MLD

Next, we sought to determine the neural mechanisms underlying the observed differences in latent cognitive processes during symbolic quantity discrimination between children with MLD and TD children. Our analysis revealed that neural responses in the right MFG mediated the relationship between symbolic response caution and group status (MLD vs. TD). This finding suggests that the deficits in response caution observed in children with MLD may be partly explained by atypical functioning in the frontal cortex (Szucs et al., 2013). Similarly, previous studies have implicated prefrontal cortical regions in problem solving deficits in MLD (Ashkenazi et al., 2012; Rosenberg-Lee et al., 2015).

This mediation effect underscores a direct link between neural activity in the MFG and behavioral manifestations of response caution deficits in children with MLD. The MFG has been linked to numerical cognition (Arsalidou et al., 2018; Koyama et al., 2017; Zacharopoulos, Sella, Cohen Kadosh, et al., 2021; Zacharopoulos, Sella, & Kadosh, 2021) as well as cognitive control and executive functioning more broadly (Diamond, 2013; Menon & D'Esposito, 2022). The observed mediation effect of the MFG suggests that impairments in cognitive control and monitoring during symbolic quantity discrimination may contribute to response caution deficits in children with MLD.

Interestingly, this mediation effect was specific to response caution during symbolic, and not non-symbolic, quantity discrimination. This finding indicates reduced neural modulation in the MFG linked to response caution deficits in children with MLD when processing symbolic numerical information, which may involve higher levels of cognitive control and abstract reasoning, compared to general magnitude processing.

Anterior cingulate cortex mediates post-error adjustment deficits in MLD

Mediation analysis also revealed that the neural distance effects in the ACC mediated the effect of post-error adjustment during symbolic quantity discrimination on MLD status, contributing to the best-fitting model. The ACC is well-established in its role in detecting errors and signaling the need for behavioral adjustments (Carter et al., 1998; Choo et al., 2023; O'Connell et al., 2007; Yeung et al., 2004) and conflict monitoring and cognitive control (Shenhav et al., 2016; van Veen et al., 2001). The role of ACC in monitoring performance and adjusting behavior suggests that children with MLD may have impaired error detection mechanisms, leading to inadequate behavioral adjustments after mistakes.

Interestingly, the right MFG emerged as a significant mediator in both the symbolic-response-caution-MLD-status and symbolic-post-error-adjustment-MLD-status relationships, which suggests that the MFG supports multiple latent cognitive mechanisms underlying symbolic quantity discrimination and math abilities. The relationship between symbolic post-error adjustment and MLD status was not significantly mediated by other brain regions, despite their reduced neural distance effects in MLD, which suggests a potential dissociation in their functional roles. For example, the inferior frontal gyrus has been implicated in inhibitory control and response selection (Cai et al., 2017; Cai et al., 2014; Goghari & MacDonald, 2009; Reckless et al., 2014; Zhang et al., 2004) as well as metacognitive monitoring of arithmetic task performance (Bellon, Fias, Ansari, et al., 2020). In contrast to these roles, the ACC may support specific process of adjusting behavior after errors in symbolic quantity discrimination.

Finally, the mediation effect of the ACC was observed for post-error adjustments during symbolic, and not non-symbolic, quantity discrimination, indicating the role of ACC when processing symbolic numerical information, which may require high-level monitoring of errors in judgements about abstract numbers. Together, our findings highlight the ACC and MFG as potential targets for interventions aimed at enhancing adaptive behavior in children with MLD.

Theoretical implications

Our findings provide novel, multidimensional support for the access deficit hypothesis of MLD (De Smedt & Gilmore, 2011; Rousselle & Noël, 2007). The preserved or even enhanced performance monitoring for non-symbolic quantities, coupled with specific deficits in symbolic numerical processing, provides further support for the access deficit in symbolic numbers in MLD. Our findings demonstrate that access deficits in MLD may extend beyond symbol-quantity mapping to encompass broader difficulties in metacognitive control during numerical problem solving.

The DDM-DPM developed in the current study revealed an important dissociation between different components of numerical processing. While evidence accumulation (drift rate), reflecting lower-level processing efficiency, showed similar patterns across MLD and TD groups, response caution and performance monitoring, representing higher-level cognitive control processes, showed format-specific deficits in children with MLD. This dissociation suggests that interventions for MLD may benefit from targeting metacognitive strategies during symbolic numerical task performance.

It is worth noting that our sample of MLD was characterized by difficulties in arithmetic fluency, which allowed us to examine the neurocognitive mechanisms underlying a specific mathematical difficulty profile. Future investigations incorporating more diverse samples with heterogenous profiles of mathematical difficulties will enhance our understanding of the latent cognitive mechanisms underlying different manifestations of MLD.

Conclusions

Our study bridges the gap between behavioral observations, latent cognitive processes, and neural mechanisms in MLD. The integration of DDM-DPM with neuroimaging revealed pronounced alterations in cognitive control and metacognitive processes including response caution and post-error adjustment in MLD. Understanding these hidden mechanisms provides insights into why children with arithmetic difficulties may struggle with mathematics despite apparently intact basic numerical processing. These findings suggest that diagnosis and remediation strategies for MLD may target not only basic numerical skills but also metacognitive processes. Future research should examine how these latent cognitive processes and their neural correlates change with learning and development (Park et al., 2024; Schwartz et al., 2021). More broadly, the latent cognitive modeling approach developed here may have implications for investigating individual differences in other cognitive domains and clinical populations.

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Figure and Table Captions

Figure 1. Drift Diffusion Model with Dynamic Performance Monitoring (DDM-DPM) model of latent behavioral dynamics underlying symbolic and non-symbolic quantity discrimination. A. *Cognitive model of latent behavioral dynamics.* In a significant advance over standard drift diffusion models, our cognitive model captured item-level effects in a continuous manner, such that drift rate depended on both individual-level and item-level effects. In addition, this model accounted for both external and internal sources of structural variability over time in trial-level response caution (decision threshold) parameter. **B.** *Graphical model of hierarchical Bayesian implementation*. The model incorporated hierarchical priors separately for mathematical learning disability (MLD) and typically developing (TD) groups and inferred parameters for both symbolic and non-symbolic condition within the same overall model to allow certain model parameters to be held constant across conditions.

Figure 2. Schematic overview of analysis. **A.** *Behavioral measures* included observed and latent behavioral measures derived from performance on quantity discrimination task in symbolic (sym) and non-symbolic (non-sym) formats. Distance effects (DEs; difference between Near and Far distance conditions) were obtained to assess quantity discrimination ability and to relate to brain measures of neural DEs. DDM-DPM (see also **Figure 1**) yielded measures of drift rate DE (rate of information accumulation for Near vs. Far trials), response caution DE (carefulness of judgments for Near vs. Far trials), and post-error adjustment (shifts in degree of confidence after error trials). **B.** *Behavioral analysis* examined whether symbolic and non-symbolic quantity

discrimination abilities, which were assessed by observed and latent behavioral measures (**Figure 2A**), are similar or different between children with mathematical learning disabilities (MLD) and typically developing (TD) children. See also **Tables 1-2** for participant characteristics for behavioral and brain imaging samples. **C.** *Brain measures* included differences in neural responses during Near vs Far distance conditions (i.e., neural DEs) of symbolic and non-symbolic quantity discrimination task. **D.** *Brain-behavior mediation analysis* examined whether the relation between latent behavior and MLD status could be explained by individual differences in brain response.

Figure 3. Symbolic and non-symbolic numerical distance effects in children with MLD compared to controls. **A.** *Main effect of format*: In analysis of variance (ANOVA) with format (symbolic, non-symbolic) as a within-subject factor and group (MLD, TD) as a between-subject factor, DE of efficiency and DE of accuracy was more negative (i.e., reduced efficiency and accuracy for Near compared to Far trials) for non-symbolic, compared to symbolic, quantity discrimination. DE of median response time (RT) was higher (i.e., slower processing speed for Near compared to Far trials) for non-symbolic, compared to symbolic, quantity discrimination. No significant main effect of group or group by format interaction was observed for any of DE measures. See also **Table 3** for results from ANOVA. Mean values are shown in larger circles and individual data are displayed in smaller circles. Error bars represent 95% confidence intervals. **B.** Scatter plots of association between symbolic and non-symbolic numerical DE and math ability (see *Methods*) in each group (blue: MLD group; red: TD group). **C.** Effect size of correlation between symbolic and non-symbolic numerical DE and math ability. Non-

significant correlations are shown in gray. **D.** Prediction of math ability from multiple observed measures of quantity discrimination in each symbolic and non-symbolic format (see also *Methods*). BF = Bayes Factor; *d* = Cohen's *d*; *n.s.* = not significant.

Figure 4. Similar and distinct latent cognitive profiles of quantity discrimination abilities in children with MLD compared to controls. **A.** *Main effect of format*: In ANOVA with format (symbolic, non-symbolic) as a within-subject factor and group (MLD, TD) as a between-subject factor. DE of drift rate was more negative (i.e., reduced drift rate for Near compared to Far trials) for non-symbolic, compared to symbolic, quantity discrimination. Post-error adjustment was greater for symbolic, compared to non-symbolic, quantity discrimination. *Main effect of group*: Greater response caution DE was found in TD compared to MLD group. *Group by format interaction*: Greater difference between MLD and TD groups was observed for symbolic, compared to non-symbolic, quantity discrimination for response caution DE. Post-error adjustment was greater for TD compared to MLD group for symbolic quantity discrimination and greater for MLD compared to TD group for non-symbolic quantity discrimination. See also **Table 4** for results from ANOVA. Mean values are shown in larger circles and individual data are displayed in smaller circles. Error bars represent 95% confidence intervals. Statistical significance and effect size from post-hoc *t*-tests for difference (Δ) between groups or formats are shown where significant group by format interaction was observed from ANOVA. **B.** Scatter plots of association between latent measures of symbolic and non-symbolic quantity discrimination and math ability (see *Methods*) in each group (blue: MLD group; red: TD group). **C.** Effect size (Spearman's rho, ρ) of

correlation between latent measures of symbolic and non-symbolic quantity discrimination and math ability. Significant correlations are shown in blue bars and non-significant correlations are shown in gray bars. **D.** Prediction of math ability from multiple latent measures of quantity discrimination in each symbolic and non-symbolic format (see also *Methods*). ** $p < .01$, *** $p < .001$; BF = Bayes Factor; d = Cohen's d; *n.s.* = not significant.

Figure 5. Neural mechanisms of latent behavioral deficits in MLD. A. *Group differences in brain activation during symbolic quantity discrimination*. Compared to TD children, children with MLD showed lower neural DE in the left anterior cingulate cortex (ACC), bilateral middle frontal gyrus (MFG), right inferior frontal gyrus (IFG), and right superior temporal gyrus (STG). **B.** *A mediation model for symbolic response caution*. The relation between symbolic response caution DE and the presence of MLD was mediated by the right MFG neural DE during symbolic quantity discrimination (indirect effect of the right MFG neural DE in the relation between symbolic response caution DE and the presence of MLD: $b = -1.11$, $se = .44$, $z = -2.53$, $p = .011$). A significant direct effect of symbolic response caution DE on the presence of MLD indicated partial mediation. The model including the right MFG region was the only model with a significant indirect effect among the regions examined (**Figure 5A**; **Tables 6-7**). **C.** *A mediation model for symbolic post-error adjustment.* The relation between symbolic post-error adjustment and the presence of MLD was mediated by the neural DE in the left ACC during symbolic quantity discrimination (indirect effect of the left ACC neural DE in the relation between post-error adjustment and the presence of MLD: $b = -1.72$,

se = .84, *z* = -2.05, *p* = .040). A significant direct effect of post-error adjustment on the presence of MLD indicated partial mediation. The model including the ACC region was the best fitting model with a significant indirect effect among the regions examined (**Figure 5A**; **Tables 6-7**). L: left. * $p < .05$, ** $p < .01$, *** $p < .001$.

Table 1. Behavioral data analysis sample: Demographics and neuropsychological measures of children with MLD (n = 34) and TD children (n = 53).

Abbreviations: BF = Bayes factor; MLD = mathematical learning disabilities; TD = typically developing; WASI = Wechsler Abbreviated Scale of Intelligence; WJ-III = Woodcock Johnson III.

Note: Boldface BF values (.3) provide evidence for H1. BF values between 0.33 and 3 provide absence of evidence (i.e., insufficient evidence for either H1 or Ho; Keysers et al., 2020).

[a]*df* = 83, [b]*df* = 84; **p* < .05, ***p* < .01, ****p* < .001.

Table 2. Brain imaging data analysis sample: Demographics and neuropsychological measures of children with MLD (n = 28) and TD children (n = 44).

Abbreviations: BF = Bayes factor; MLD = mathematical learning disabilities; TD = typically developing; WASI = Wechsler Abbreviated Scale of Intelligence; WJ-III = Woodcock Johnson III.

Note: Boldface BF values (.3) provide evidence for H1. BF values between 0.33 and 3 provide absence of evidence (i.e., insufficient evidence for either H1 or Ho; Keysers et al., 2020).

[a]*df* = 68, [b]*df* = 69; ****p* < .001.

Table 3. Main effects and interactions of Group (MLD, TD) and Format (symbolic, non-symbolic) on children's observed numerical distance effects (DEs; n = 85-87).

Abbreviations: BF = Bayes factor; MLD = children with mathematical learning disabilities; TD = typically developing children.

***p < .001. Bolded Bayes Factor (BF) (>3) provides evidence for H_1. BF values between .33 and 3 provide absence of evidence (i.e., insufficient evidence for either H_1 or H_o). BF values below .33 provide evidence of absence (evidence for H_o) (Keysers et al., 2020).

Table 4. Main effects and interactions of Group (MLD, TD) and Format (symbolic, non-symbolic) on children's latent cognitive processes (n = 82-87).

Abbreviations: BF = Bayes factor; DE = distance effect; MLD = children with mathematical learning disabilities; TD = typically developing children.

*p < .05, **p < .01, ***p < .001. Bolded Bayes Factor (BF) (>3) provides evidence for H_1. BF values between .33 and 3 provide absence of evidence (i.e., insufficient evidence for either H_1 or H_o). BF values below .33 provide evidence of absence (evidence for H_o) (Keysers et al., 2020).

Table 5. Model comparison between multiple regression analysis including symbolic and/or non-symbolic latent measures as predictors of math ability (n = 82).

Notes: DE = distance effect; RT = reaction time. * p < .05; ** p < .01; *** p <.001. Bolded Bayes factor (BF) (>3) provides evidence for H_1. BF values between .33 and 3 provide absence of evidence (i.e., insufficient evidence for either H_1 or H_o). BF values below .33 provide evidence of absence (evidence for H_o) (Keysers et al., 2020).

Table 6. Group differences in brain activation during quantity discrimination (Near vs Far, i.e., neural distance effect [DE]; n = 72).

Abbreviations: ACC, anterior cingulate cortex; IFG, inferior frontal gyrus; MFG, middle frontal gyrus; MLD = children with math learning disabilities; STG, superior temporal gyrus; TD = typically developing children; L: left; R: right.

Table 7. Comparison of model fit of structural equation models (n = 69-72).

Abbreviations: ACC, anterior cingulate cortex; AIC, Akaike information criterion; BIC, Bayesian information criterion; DE, distance effect; IFG, inferior frontal gyrus; LBMI: latent behavioral measure of interest; MFG, middle frontal gyrus; MLD, presence of math learning disability; ROI, region of interest; STG, superior temporal gyrus; L: left, R: right.

Notes: Models were constructed to investigate how neural DE (beta estimates of Near minus Far distance) of an ROI (or estimated latent variable across a set of ROIs) mediates the influence of a LBMI on MLD status during symbolic quantity discrimination. Statistical significance (*p* values) of path estimates (*a*, *b*, *c'*) is shown. Significant direct and indirect (*ab)* effects are shown in bold. Values of AIC and BIC in bold and italics highlight the model with the lowest scores (best-fitting model) among models with significant indirect effects.

For transparency, FDR-corrected *p* values are shown in parenthesis for the models of individual ROIs. As the models specifically tested the mediation of the neural DE of an ROI in the relationship between LBMI and MLD status, rather than exploration of potential pathways, in a matched sample of children, statistical inference was based on uncorrected *p* values.

[1] an ROI identified from the whole-brain analysis of group difference in neural DE during symbolic quantity discrimination (**Figure 5A**; **Table 6**).

[2] a latent variable estimated from five ROIs identified from the whole-brain analysis of group difference in neural DE during symbolic quantity discrimination (**Figure 5A**; **Table 6**).

Table 1. Behavioral data analysis sample: Demographics and neuropsychological measures of children with MLD (n = 34) and TD children (n = 53).

	MLD	TD	χ^2 test or two-sample *t*-test			
	M (SD)	*M (SD)*	χ^2_1 or $t(85)$	*p*	φ or Cohen's *d*	*BF*
Female to Male ratio	17 : 17	32 : 21	.53	.465	.08	.59
Age	8.20 (.74)	8.23 (.56)	-.20	.846	-.04	.23
WASI:						
Verbal IQ	107.38 (13.94)	110.17 (11.12)	-1.03	.305	-.23	.36
Performance IQ	103.53 (15.64)	107.32 (13.59)	-1.20	.235	-.26	.43
Full-Scale IQ	105.85 (14.20)	109.70 (11.09)	-1.41	.161	-.31	.54
WJ-III:						
Math Fluency	85.41 (4.15)	104.38 (9.06)	-11.45***	<.001	-2.51	**4.87**
Calculation	97.94 (11.58)	109.04 (12.98)	-4.06***	<.001	-.89	**>100**
Applied Problems	97.88 (13.76)	108.96 (10.56)	-4.24***	<.001	.93	**>100**
Letter-Word Identification	107.42 (11.34)	111.85 (8.55)	-2.04[a]*	.044	.45	1.39
Word Attack	103.58 (8.20)	109.08 (8.36)	-2.99[b]**	.004	.66	**10.11**
Math Composite	91.39 (6.44)	105.06 (8.24)	-8.19***	<.001	-1.80	**>100**

Math Anxiety	1.14 (.64)	.97 (.65)	1.21^{b}	.231	.27	.43

Abbreviations: BF = Bayes factor; MLD = mathematical learning disabilities; TD = typically developing; WASI = Wechsler Abbreviated Scale of Intelligence; WJ-III = Woodcock Johnson III.

$^{a}df = 83$, $^{b}df = 84$; $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$. Boldface BF values (>3) provide evidence for H_1. BF values between .33 and 3 provide absence of evidence (i.e., insufficient evidence for either H_1 or H_0). BF values below .33 provide evidence of absence (evidence for H_o) (Keysers et al., 2020).

Table 2. Brain imaging data analysis sample: Demographics and neuropsychological measures of children with MLD (n = 28) and TD children (n = 44).

	MLD	TD	χ^2 test or two-sample *t*-test			
	M (SD)	*M (SD)*	χ^2_1 or $t(70)$	*p*	φ or Cohen's *d*	*BF*
Female to Male ratio	15 : 13	26 : 18	.05	.828	< .01	.46
Age	8.24 (.72)	8.21 (.53)	.21	.835	.05	.25
WASI:						
Verbal IQ	106.68 (11.59)	109.77 (11.61)	-1.10	.274	-.27	.42
Performance IQ	103.96 (15.98)	105.73 (13.22)	-.51	.613	-.12	.28
Full-Scale IQ	105.75 (12.80)	108.55 (11.10)	-.98	.330	-.24	.37
WJ-III:						
Math Fluency	85.89 (3.58)	103.73 (8.04)	-11.04***	<.001	-2.67	**6.53**
Calculation	97.86 (9.28)	108.52 (12.94)	-3.78***	<.001	-.91	**79.73**
Applied Problems	98.14 (13.45)	109.32 (10.74)	-3.90***	<.001	-.94	**>100**
Letter-Word Identification	109.89 (10.49)	111.54 (8.85)	-.71[a]	.483	-.17	.31
Word Attack	105.33 (7.80)	108.82 (9.01)	-1.66[b]	.101	-.41	.81

Math Composite	91.66 (5.62)	104.51 (7.62)	-7.68***	<.001	-1.86	**>100**
Math Anxiety	1.11 (.67)	.99 (.59)	.83	.411	.20	.33

Abbreviations: BF = Bayes factor; MLD = mathematical learning disabilities; TD = typically developing; WASI = Wechsler Abbreviated Scale of Intelligence; WJ-III = Woodcock Johnson III.

[a]$df = 68$, [b]$df = 69$; ***$p < .001$. Boldface BF values (>3) provide evidence for H_1. BF values between .33 and 3 provide absence of evidence (i.e., insufficient evidence for either H_1 or H_0) (Keysers et al., 2020).

Table 3. Main effects and interactions of Group (MLD, TD) and Format (symbolic, non-symbolic) on children's observed numerical distance effects (DEs; n = 85-87).

Numerical DE based on		F	df	p	η_p^2	BF
Efficiency	Group	3.63	1,85	.060	.04	.64
	Format	117.14***	1,85	<.001	.58	**>100**
	Group * Format	1.32	1,85	.253	.02	.41
Accuracy	Group	.15	1,83	.696	<.001	.19
	Format	105.59***	1,83	<.001	.56	**>100**
	Group * Format	1.45	1,83	.232	.02	.45
Reaction time	Group	2.19	1,85	.142	.03	.46
	Format	13.87***	1,85	<.001	.14	**>100**
	Group * Format	.92	1,85	.339	.01	.42

Abbreviations: BF = Bayes factor; MLD = children with mathematical learning disabilities; TD = typically developing children.

***p < .001. Bolded Bayes Factor (BF) (>3) provides evidence for H_1. BF values between .33 and 3 provide absence of evidence (i.e., insufficient evidence for either H_1 or H_o). BF values below .33 provide evidence of absence (evidence for H_o) (Keysers et al., 2020).

Table 4. Main effects and interactions of Group (MLD, TD) and Format (symbolic, non-symbolic) on children's latent cognitive processes (n = 82-87).

Latent behavioral measure		*F*	*df*	*p*	η_p^2	*BF*
Drift rate DE	Group	2.57	1,85	.113	.03	.42
	Format	157.64***	1,85	<.001	.65	**>100**
	Group * Format	1.71	1,85	.195	.02	.49
Response caution DE	Group	13.39***	1,80	<.001	.14	**15.02**
	Format	8.77**	1,80	.004	.10	**13.86**
	Group * Format	6.57*	1,80	.012	.08	**8.29**
Post-error adjustment	Group	2.59	1,85	.111	.03	.32
	Format	182.07***	1,85	<.001	.68	**>100**
	Group * Format	36.92***	1,85	<.001	.30	**>100**

Abbreviations: BF = Bayes factor; DE = distance effect; MLD = children with mathematical learning disabilities; TD = typically developing children.

*p < .05, **p < .01, ***p < .001. Bolded Bayes Factor (BF) (>3) provides evidence for H_1. BF values between .33 and 3 provide absence of evidence (i.e., insufficient evidence for either H_1 or H_o). BF values below .33 provide evidence of absence (evidence for H_o) (Keysers et al., 2020).

Table 5. Model comparison between multiple regression analysis including symbolic and/or non-symbolic latent measures as predictors of math ability (n = 82).

Model fit	Adjusted R^2	F	df	p	BF
Model 1 [*symbolic latent measures*]: (1 + symbolic drift rate DE + symbolic response caution DE + symbolic post-error adjustment)	.17	6.39***	3, 78	<.001	**44.48**
Model 2 [*non-symbolic latent measures*]: (1 + non-symbolic drift rate DE + non-symbolic response caution DE + non-symbolic post-error adjustment)	.06	2.86*	3, 78	.042	.91
Model 3 [*symbolic + non-symbolic latent measures*]: (Model 1 + Model 2)	.20	4.32***	6, 75	<.001	**25.48**

Model comparison	ΔR^2	F	df	p	BF
Model 3 vs. **Model 1** [*additional variance explained by non-symbolic latent measures*]	.06	1.99	3	.122	.57
Model 3 vs. **Model 2** [*additional variance explained by symbolic latent measures*]	.16	5.30**	3	.002	**28.06**

Abbreviation: DE = distance effect.

**** p < .05; ** p < .01; *** p <.001. Bolded Bayes factor (BF) (>3) provides evidence for H_1. BF values between .33 and 3 provide absence of evidence (i.e., insufficient evidence for either H_1 or H_0) (Keysers et al., 2020).***

Table 6. Group differences in brain activation during quantity discrimination (Near vs Far, i.e., neural distance effect [DE]; n = 72).

		k	*t*	MNI (*x*,*y*,*z*)	region
Symbolic	TD > MLD	50	4.37	58 28 4	R IFG
			4.08	54 34 0	
		172	4.1	-2 32 12	L ACC
			3.96	8 26 16	
			3.7	-2 28 20	
		69	3.79	40 44 2	R MFG
		37	3.75	44 -20 8	R STG
		63	3.65	-34 38 16	L MFG
			3.61	-42 44 18	
	MLD > TD			No significant cluster	
Non-Symbolic	TD > MLD			No significant cluster	
	MLD > TD			No significant cluster	

Abbreviations: ACC, anterior cingulate cortex; IFG, inferior frontal gyrus; MFG, middle frontal gyrus; MLD = children with math learning disabilities; STG, superior temporal gyrus; TD = typically developing children; L: left; R: right.

1404 **Table 7**. Comparison of model fit of structural equation models (*n* = 69-72).

	MLD~ROI~LBMI	ROI ~LBMI	MLD ~ROI	MLD ~LBMI	AIC	BIC
	ab	*a*	*b*	*c'*		
LBMI: *symbolic response caution DE*						
L ACC[1]	.087 (.145)	**.024** (**.040**)	**.005** (**.006**)	**.008** (**.008**)	250.94	262.11
L MFG[1]	.076 (.145)	**.008** (**.020**)	**.019** (**.019**)	**.005** (**.007**)	228.92	240.10
R MFG[1]	**.011** (.055)	**<.001** (**<.005**)	**.003** (**.005**)	**.006** (**.007**)	***253.90***	***265.07***
R IFG[1]	.412 (.412)	.349 (.349)	**.001** (**.002**)	**<.001** (<**.002**)	241.77	252.94
R STG[1]	.348 (.412)	.295 (.349)	**.001** (**.002**)	**<.001** (<**.002**)	245.03	256.20
5-ROI[2]	.068	**.034**	**.001**	**.028**	737.74	769.81
LBMI: *symbolic post-error adjustment*						
L ACC[1]	**.040** (.103)	**.012** (**.030**)	**.001** (**.001**)	**.010** (**.010**)	***260.65***	***272.04***
L MFG[1]	.113 (.188)	.087 (.145)	**.002** (**.002**)	**.003** (**.005**)	237.85	249.24
R MFG[1]	**.041** (.103)	**.011** (**.030**)	**.001** (**.001**)	**.005** (**.006**)	265.63	277.02
R IFG[1]	.611 (.611)	.597 (.597)	**<.001** (<**.001**)	**<.001** (<**.002**)	256.65	268.04

R STG[1]	.247 (.309)	.211 (.264)	**<.001** (<**.001**)	**.001** (**.002**)	258.57	269.95
5-ROI[2]	.117	.094	**<.001**	**.002**	783.66	816.47

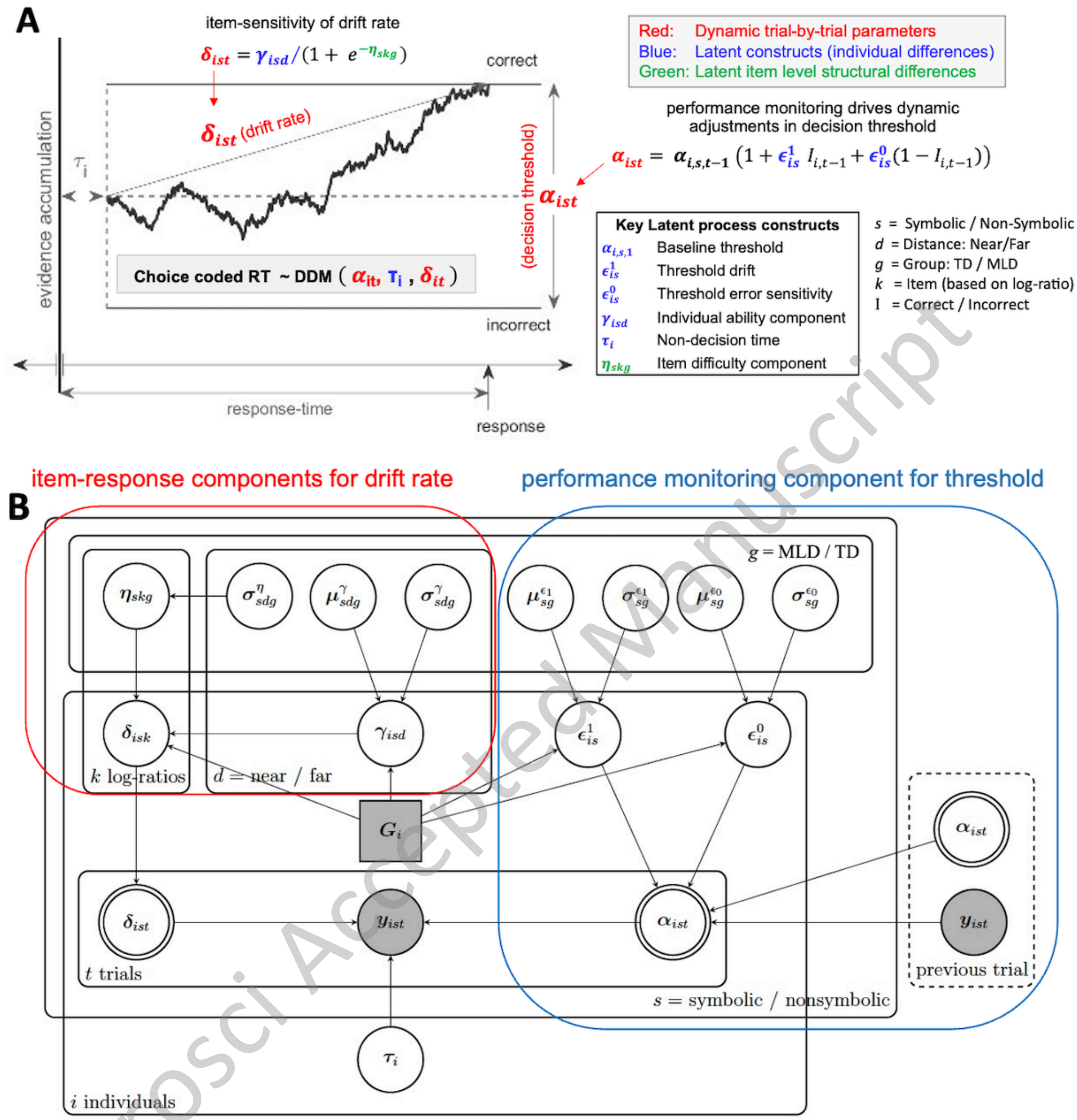
Abbreviations: ACC, anterior cingulate cortex; AIC, Akaike information criterion; BIC, Bayesian information criterion; DE, distance effect; IFG, inferior frontal gyrus; LBMI: latent behavioral measure of interest; MFG, middle frontal gyrus; MLD, presence of math learning disability; ROI, region of interest; STG, superior temporal gyrus; L: left, R: right.

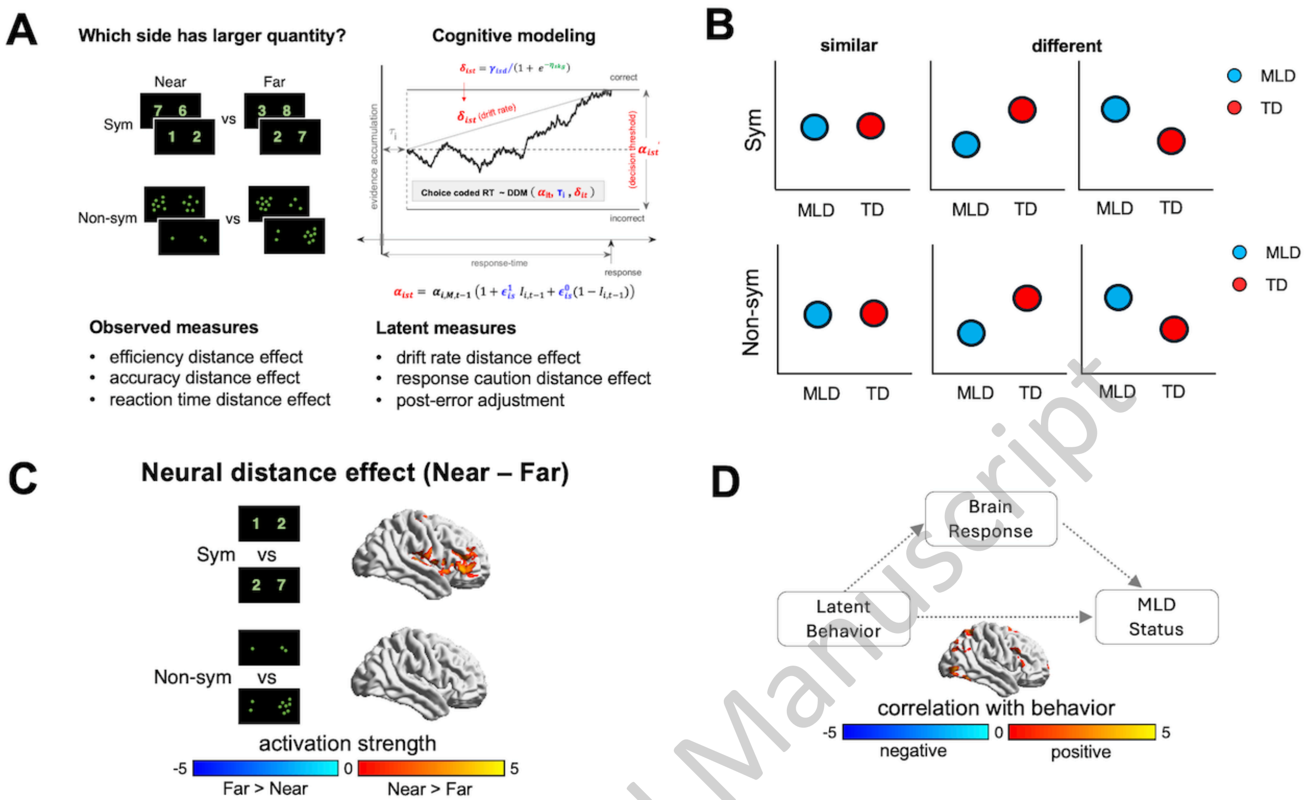
Notes: Models were constructed to investigate how neural DE (beta estimates of Near minus Far distance) of an ROI (or estimated latent variable across a set of ROIs) mediates the influence of a LBMI on MLD status during symbolic quantity discrimination. Statistical significance (*p* values) of path estimates (*a*, *b*, *c'*) is shown. Significant direct and indirect (*ab)* effects are shown in bold. Values of AIC and BIC in bold and italics highlight the model with the lowest scores (best-fitting model) among models with significant indirect effects.

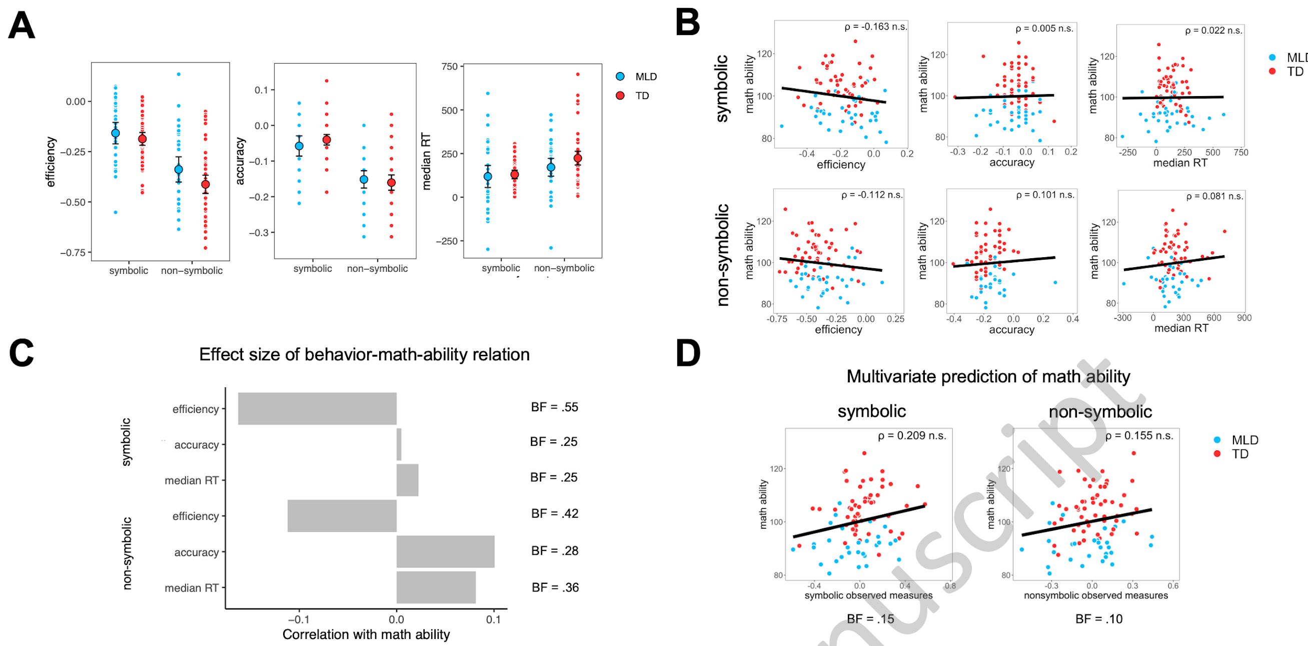
For transparency, FDR-corrected *p* values are shown in parenthesis for the models of individual ROIs. As the models specifically tested the mediation of the neural DE of an ROI in the relationship between LBMI and MLD status, rather than exploration of potential pathways, in a matched sample of children, statistical inference was based on uncorrected *p* values.

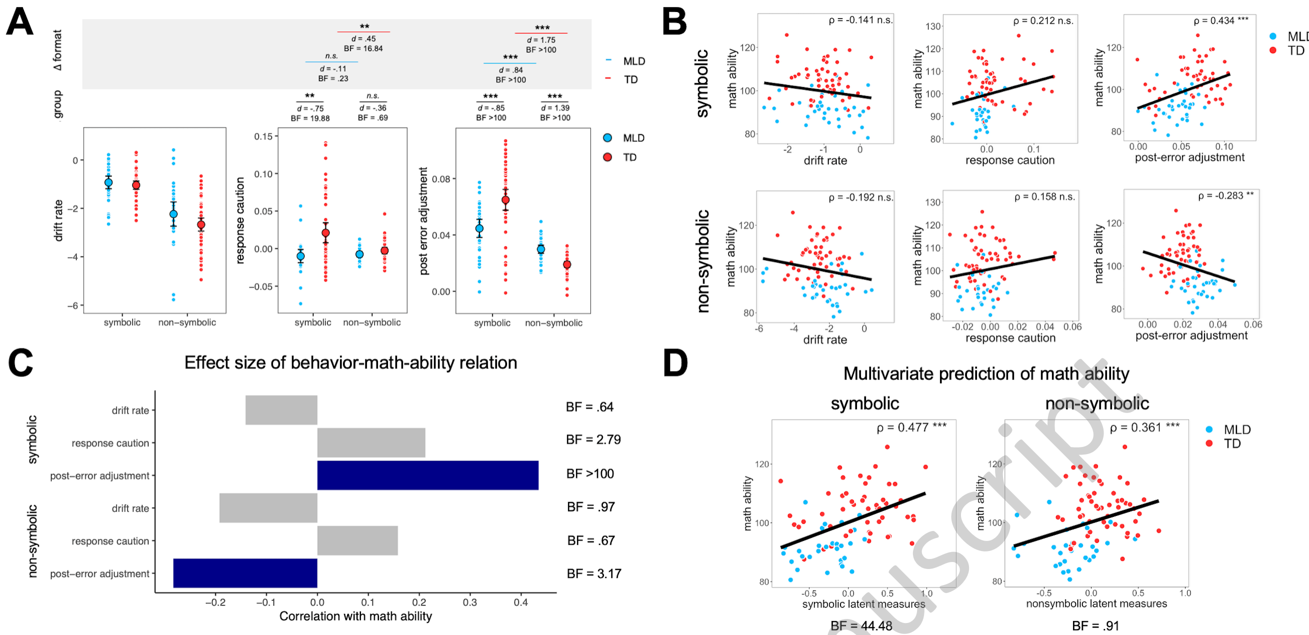
[1] an ROI identified from the whole-brain analysis of group difference in neural DE during symbolic quantity discrimination (**Figure 5A**; **Table 6**).

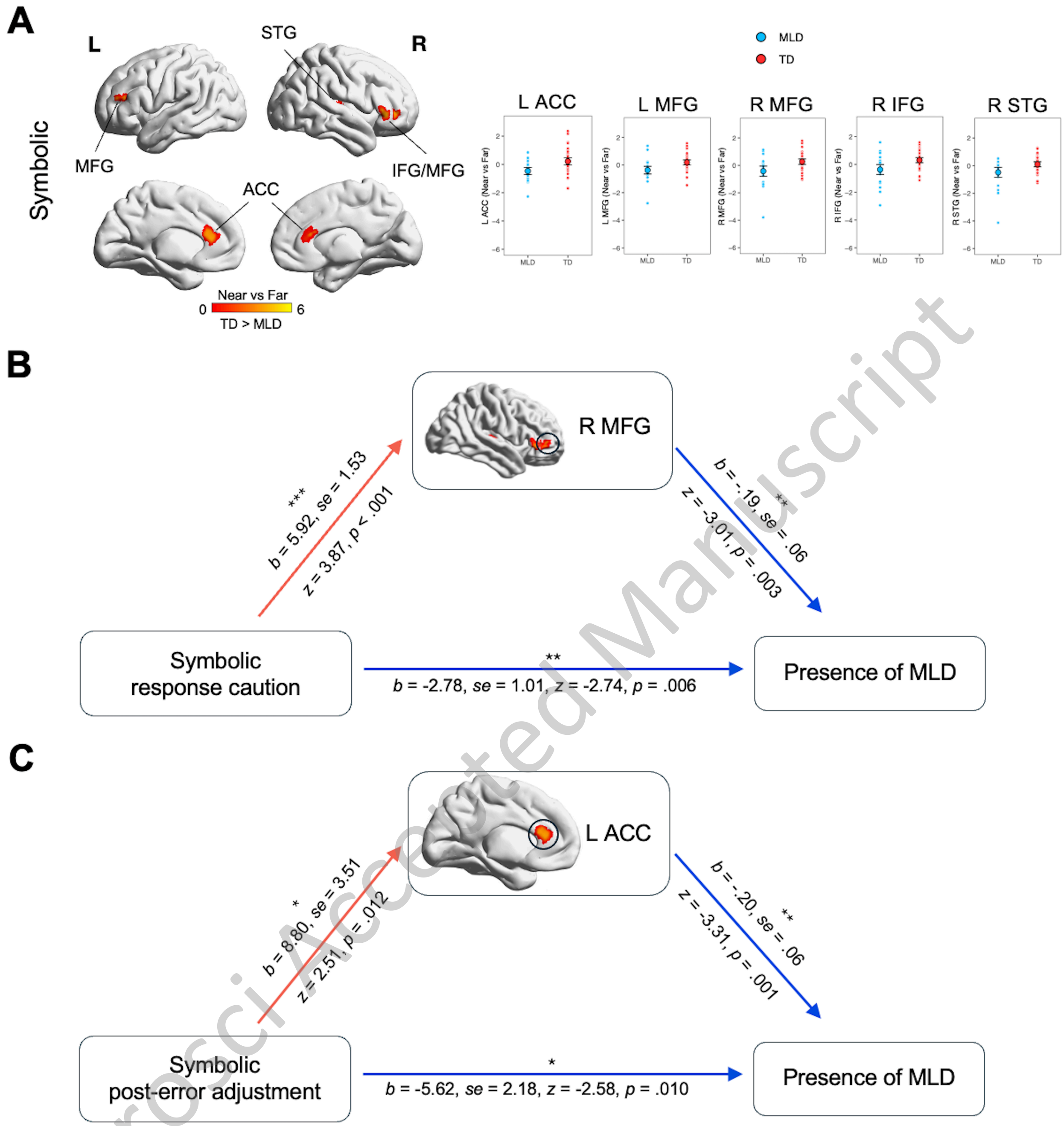
[2] a latent variable estimated from five ROIs identified from the whole-brain analysis of group difference in neural DE during symbolic quantity discrimination (**Figure 5A**; **Table 6**).


A
item-sensitivity of drift rate
$\delta_{ist} = \gamma_{isd}/(1+e^{-\eta_{skg}})$
correct
δ_{ist} (drift rate)
evidence accumulation
τ_i
(decision threshold)
α_{ist}
Choice coded RT ~ DDM (α_{it}, τ_i , δ_{it})
incorrect
response-time
response
Red: Dynamic trial-by-trial parameters
Blue: Latent constructs (individual differences)
Green: Latent item level structural differences
performance monitoring drives dynamic adjustments in decision threshold
$\alpha_{ist} = \alpha_{i,s,t-1}\,(1+\epsilon^1_{is}\, I_{i,t-1}+\epsilon^0_{is}(1-I_{i,t-1}))$
Key Latent process constructs
$\alpha_{i,s,1}$ Baseline threshold
ϵ^1_{is} Threshold drift
ϵ^0_{is} Threshold error sensitivity
γ_{isd} Individual ability component
τ_i Non-decision time
η_{skg} Item difficulty component
s = Symbolic / Non-Symbolic
d = Distance: Near/Far
g = Group: TD / MLD
k = Item (based on log-ratio)
I = Correct / Incorrect
item-response components for drift rate
performance monitoring component for threshold
B
g = MLD / TD
η_{skg}
σ^{η}_{sdg}
μ^{γ}_{sdg}
σ^{γ}_{sdg}
$\mu^{\epsilon1}_{sg}$
$\sigma^{\epsilon1}_{sg}$
$\mu^{\epsilon0}_{sg}$
$\sigma^{\epsilon0}_{sg}$
δ_{isk}
γ_{isd}
ϵ^1_{is}
ϵ^0_{is}
k log-ratios
d = near / far
G_i
α_{ist}
y_{ist}
δ_{ist}
y_{ist}
α_{ist}
t trials
previous trial
s = symbolic / nonsymbolic
τ_i
i individuals


A
Which side has larger quantity?
Near
Far
Sym
vs
Non-sym
vs
Cognitive modeling
correct
incorrect
evidence accumulation
response-time
response
Choice coded RT ~ DDM
Observed measures
• efficiency distance effect
• accuracy distance effect
• reaction time distance effect
Latent measures
• drift rate distance effect
• response caution distance effect
• post-error adjustment
B
similar
different
Sym
Non-sym
MLD
TD
C
Neural distance effect (Near – Far)
Sym vs
Non-sym vs
activation strength
-5
0
5
Far > Near
Near > Far
D
Brain Response
Latent Behavior
MLD Status
correlation with behavior
-5
0
5
negative
positive


A
efficiency
accuracy
median RT
symbolic
non-symbolic
MLD
TD
B
math ability
ρ = -0.163 n.s.
ρ = 0.005 n.s.
ρ = 0.022 n.s.
ρ = -0.112 n.s.
ρ = 0.101 n.s.
ρ = 0.081 n.s.
C
Effect size of behavior-math-ability relation
BF = .55
BF = .25
BF = .25
BF = .42
BF = .28
BF = .36
Correlation with math ability
D
Multivariate prediction of math ability
ρ = 0.209 n.s.
ρ = 0.155 n.s.
symbolic observed measures
nonsymbolic observed measures
BF = .15
BF = .10


A
Δ format
group
MLD
TD
drift rate
response caution
post error adjustment
symbolic
non−symbolic
B
symbolic
non-symbolic
math ability
drift rate
response caution
post-error adjustment
ρ = -0.141 n.s.
ρ = 0.212 n.s.
ρ = 0.434 ***
ρ = -0.192 n.s.
ρ = 0.158 n.s.
ρ = -0.283 **
C
Effect size of behavior-math-ability relation
drift rate
response caution
post-error adjustment
BF = .64
BF = 2.79
BF >100
BF = .97
BF = .67
BF = 3.17
Correlation with math ability
D
Multivariate prediction of math ability
symbolic
non-symbolic
ρ = 0.477 ***
ρ = 0.361 ***
symbolic latent measures
nonsymbolic latent measures
BF = 44.48
BF = .91


A
L
STG
R
Symbolic
MFG
IFG/MFG
ACC
Near vs Far
0
6
TD > MLD
MLD
TD
L ACC
L MFG
R MFG
R IFG
R STG
B
R MFG
***
b = 5.92, se = 1.53
z = 3.87, p < .001
b = -.19, se = .06
**
z = -3.01, p = .003
Symbolic
response caution
**
b = -2.78, se = 1.01, z = -2.74, p = .006
Presence of MLD
C
L ACC
*
b = 8.80, se = 3.51
z = 2.51, p = .012
b = -.20, se = .06
**
z = -3.31, p = .001
Symbolic
post-error adjustment
*
b = -5.62, se = 2.18, z = -2.58, p = .010
Presence of MLD