Auditory category learning in children with dyslexia

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Abstract

Purpose: Developmental dyslexia is proposed to involve selective procedural memory deficits with intact declarative memory. Recent research in the domain of category learning has demonstrated that adults with dyslexia have selective deficits in information-integration category learning that is proposed to rely on procedural learning mechanisms and unaffected rule-based category learning that is proposed to rely on declarative, hypothesis testing mechanisms. Importantly, learning mechanisms also change across development, with distinct developmental trajectories in both procedural and declarative learning mechanisms. It is unclear how dyslexia in childhood should influence auditory category learning, a critical skill for speech perception and reading development.

Method: We examined auditory category learning performance and strategies in 7-12-year-old children with dyslexia (*n* = 25, 9 Females, 16 Males) and typically developing controls (*n* = 25, 13 Females, 12 Males).

Results: We found that children with dyslexia have a rule-based category learning deficit, rather than the selective information-integration learning deficit observed in prior work in adults with dyslexia.

Conclusions: These results suggest that the important skill of auditory category learning is impacted in children with dyslexia and throughout development, individuals with dyslexia may develop compensatory strategies that preserve declarative learning while developing difficulties in procedural learning.

Developmental dyslexia is a highly prevalent learning disorder in children, impacting between 3 and 20% of school-age children (Shaywitz, 1996; Snowling, 2013). Most saliently, dyslexia affects reading abilities, but dyslexia is also proposed to have more general effects on learning and perception, especially in the domain of procedural learning. Here, we examine how children with and without dyslexia, matched by age and nonverbal IQ, learn novel auditory categories, an important skill linked to first and second language acquisition (Holt & Lotto, 2006; Kuhl, 2000; Liu & Holt, 2011; Myers & Swan, 2012; Wiener et al., 2019) that may be critical in the ability to map sounds to letters when learning to read.

Developmental Dyslexia

Developmental dyslexia is associated with impairments in phonological processing (Boets et al., 2013), temporal processing in speech and non-speech (Vandermosten et al., 2010), motor-based procedural learning (Lum et al., 2013; Vicari et al., 2005), statistical learning of auditory sequences (Gabay, Thiessen, et al., 2015), and auditory category learning (Gabay et al., 2023; Gabay & Holt, 2015).

One hypothesis of dysfunction in dyslexia suggests there are auditory and phonological processing deficits (Share, 2021; Stanovich, 1988; Tallal, 1980; Zoccolotti, 2022). One reason for these deficits could be in the inability to recognize common stimulus features needed to create categorical representations. As a child learns language, the brain processes statistical regularities in the speech environment to identify speech sounds that are common and therefore important (Kuhl et al., 1992). Individuals with dyslexia exhibit abnormalities in statistical learning in a variety of contexts (for review, see Schmalz et al., 2017). For example, reduced statistical learning in dyslexia is present in visual tasks (e.g., novel symbols and faces; Sigurdardottir et al., 2017) and in auditory tasks (e.g., tones and syllables; Gabay, Thiessen, et al., 2015). This difficulty in recognizing repeated stimulus elements likely impacts reading acquisition, as a child learns to associate various versions of a letter form with its respective speech sound category. If the brain is unable to form categories either in the speech sound domain or in the recognition of the letter shape, children are unlikely to achieve fluency.

Another hypothesis suggests that dyslexia is marked by procedural deficits (Nicolson et al., 2010; Nicolson & Fawcett, 2007). According to the Procedural Deficit Hypothesis (Lum et al., 2013; Ullman, 2004; Ullman et al., 2017), dyslexia is associated with general procedural learning deficits that impair the ability to learn via slower associative mechanisms such as reinforcement learning. In dyslexia, this learning deficit is proposed to specifically affect the ability to learn mappings between print and sound (Castles et al., 2018; Snowling et al., 2020).

Category Learning in Dyslexia

In the current study, we leverage an artificial auditory category learning approach to better understand the nature of learning deficits in dyslexia in children. Specifically, we examine learning of categories that are argued to optimally rely on either declarative or procedural learning systems. Based on the Competition of Verbal and Implicit Systems theory (COVIS; Ashby et al., 1998), researchers have argued that categories with different structures rely on distinct neural and computational mechanisms. Specifically, categories that require selective attention to individual dimensions to create rules defining the categories (rule-based [RB] categories) are argued to optimally involve explicit, declarative mechanisms, whereas categories that require integration across multiple dimensions (information-integration [II] categories) are argued to optimally involve implicit, procedural learning mechanisms. This theory has been expanded to the auditory modality and specifically to speech category learning (Chandrasekaran et al., 2014). While often studied in artificial contexts, some real-world categories may be aligned with these RB and II definitions. For example, speech sound categories (e.g., /b/ versus /p/) may be a type of II category as they are multidimensional and cannot easily be described by rules, whereas ranges of opera singers (e.g., soprano versus alto) may be a type of RB category as one can identify the category by selectively attending to the vocal range of the singer.

It is important to note that evidence for these categories being learned with separate systems does not have unequivocal empirical support (Newell et al., 2011). Additionally, both RB and II categories *can* be learned to some extent with declarative strategies (Donkin et al., 2014) and steps should be taken to ensure that strategies are identifiable from participants' response data (Edmunds et al., 2018).

Some work has been done on category learning in adults with dyslexia or general reading difficulties. Adults with dyslexia are impaired at speech (Banai & Ahissar, 2018) and nonspeech category learning (Gabay, Vakil, et al., 2015; Gabay & Holt, 2015; Gertsovski & Ahissar, 2022). For both nonspeech auditory categories and visual categories, adults with dyslexia have selective deficits in category learning linked with procedural or implicit processes (II categories), but preserved learning linked with declarative or explicit processes (RB categories; Gabay et al., 2023; Sperling et al., 2004). Gabay et al. (2023) demonstrated that this selective learning deficit was due to the inability of adults with dyslexia to use optimal procedural categorization strategies during II learning. In contrast, adults with dyslexia were able to use conjunctive rule-based strategies during RB learning just as well as controls. Possibly related to their ability to learn complex auditory categories via feedback, adults with dyslexia are also impaired in reinforcement learning (Gabay, 2021; Massarwe et al., 2022). In all, these findings are generally aligned with the Procedural Deficit Hypothesis. Importantly, RB and II auditory category learning have not been directly examined in children with dyslexia. It is unclear whether learning patterns in adults with dyslexia are also present in childhood – we address this question directly in the current research.

Developmental Trajectory of Category Learning

Importantly, both RB and II learning undergo substantial changes across development. Children are generally worse at RB learning relative to adults, perseverating with suboptimal rules or using inappropriate guessing strategies (Rabi & Minda, 2014; Reetzke et al., 2016; Roark et al., 2023). Evidence for the developmental trajectory of II learning is more mixed. Some prior work has demonstrated that children are generally worse at II learning relative to adults (Huang-Pollock et al., 2011; Roark et al., 2023; Roark & Holt, 2019), while other work has demonstrated that children can be just as successful as adults for categories that cannot clearly be described by rules (Minda et al., 2008). As a result, it is possible that *children* with dyslexia may demonstrate different learning patterns compared to adults with dyslexia. RB and II category learning have not yet been examined in children with dyslexia, but learning is argued to be a core component of the dyslexia deficit (Castles et al., 2018; Snowling et al., 2020; Ullman et al., 2017). Below, we outline three possible patterns of results in children that highlight the intersection of the development of category learning and learning in dyslexia.

Predictions

First, it is possible that children with dyslexia will demonstrate similar patterns as adults with dyslexia – children, like adults, will have impaired II learning but intact RB learning, consistent with the Procedural Deficit Hypothesis. This possibility would also be supported by a specific inability of children with dyslexia, like adults, to find and use II-optimal procedural strategies, with intact RB-optimal rule-based strategies. This pattern would suggest that despite general category learning mechanisms undergoing substantial change across development, the fundamental aspects that are affected in dyslexia are present in both childhood and adulthood. Specifically, this pattern would suggest that procedural learning deficits in dyslexia are persistent throughout development.

An alternative pattern is that children with dyslexia, unlike adults, will demonstrate a general deficit in category learning. This pattern would suggest that over the course of development, adults with dyslexia may find compensatory strategies to preserve RB learning. This prediction is also consistent with the idea that sound representations are variable and unstable in dyslexia and therefore are unable to be reinforced by feedback (Centanni et al., 2018; Hornickel & Kraus, 2013; Neef et al., 2017). If children are unable to find optimal rules, this would impede both RB and II learning. This is also consistent with views of other disorders such as ADHD in building representations through general associations between stimuli and responses (Huang-Pollock et al., 2011). This pattern would suggest that dyslexia interacts with development to impact category learning ability, with children and adults with dyslexia worse than their age-matched peers at II category learning, but only children being impaired at RB learning, as adults are able to find compensatory strategies with enhanced selective attention abilities relative to children.

Finally, it is possible that the developmental patterns of category learning will outweigh any potential differences between typically developing children and children with dyslexia. Because children are generally worse at RB *and* II learning than adults, it is possible that the circuits that differentiate adults with dyslexia from controls are still developing in both typically developing children and children with dyslexia. If this is the case, then both typically developing children and children with dyslexia may demonstrate difficulty in learning, accompanied by the use of suboptimal RB strategies and exploratory/guessing strategies (Blanco & Sloutsky, 2021a;

Jones & Dekker, 2018; Liquin & Gopnik, 2022; Rabi et al., 2015; Rabi & Minda, 2014; Roark et al., 2023; Roark & Holt, 2019). As a result, there may be no significant differences between children with dyslexia and typically developing children and that differences between these groups may emerge later in development, once declarative and procedural category learning abilities have matured.

Method

Participants

We examined auditory category learning in 7-12-year-old children comparing children with dyslexia (n = 25, M = 10.1, SD = 1.48) to age-matched typically developing children (n = 25, M = 10.0, SD = 1.38). We recruited native English-speaking children throughout the United States through online advertisements as part of a larger study on stimulus processing in dyslexia. All procedures were approved by the Texas Christian University Institutional Review Board, parental consent was obtained during an online screening survey, and verbal assent was obtained from each child. All aspects of the study were conducted virtually using Zoom. The category learning tasks were administered via the Gorilla Experiment Builder (Anwyl-Irvine et al., 2020). To be eligible for the study, children needed to have no history of neurological disorders (e.g., ADHD, epilepsy, traumatic brain injury).

Eligible children completed a virtual assessment session where a trained researcher administered a series of standardized assessments in the same order for all participants. Children completed measures of nonverbal IQ (Matrices subtest of the KBIT-2, Kaufman & Kaufman, 2004) and reading skills (untimed and timed single-word reading and decoding tests, Torgesen et al., 2012; Woodcock, 2011; Word Identification and Word Attack subtests of Woodcock Reading Mastery Test [WRMT-3], Woodcock, 2011; Sight Word Efficiency and Phonemic

Decoding Efficiency subtests of the Test of Word Reading Efficiency [TOWRE-2], Torgesen et al., 2012; reading automaticity, Rapid Digit Naming and Rapid Letter Naming [RAN/RAS], Wolf & Denckla, 2005). Children were determined to be eligible for further sessions if they achieved a standard score of 85 or higher on the measure of nonverbal IQ. Of the 97 children that were initially assessed for eligibility, nine were excluded for low nonverbal IQ, 11 were excluded for not meeting requirements for reading/phonemic ability (see below), two were excluded for being a typically developing sibling of a child with dyslexia, one was excluded for failing to complete the categorization tasks within a reasonable amount of time, and 11 were lost to attrition. We excluded any participants who did not complete both category learning tasks. Among this sample, 25 children with dyslexia (9 Females, 16 Males) completed both category learning tasks. Twenty-five typically developing children (13 Females, 12 Males) were selected from the sample of 36 control children who completed both tasks based on age-matching to the children with dyslexia. Children with dyslexia were required to score below a standard score of 90 on at least two of the four measures of reading/phonemic ability (Table 1). Children with dyslexia had significantly lower scores on Word Attack ($p < .0001$), Word ID ($p < .0001$), Phonemic Decoding Efficiency ($p < .0001$), and Sight Word Efficiency ($p < .0001$) measures compared with controls. Children with dyslexia also had significantly lower nonverbal IQ scores compared with controls selected based on age-matching. Though all children were required to meet a nonverbal IQ criterion, potential differences between the groups could affect interpretations of any differences in category learning. As such, we separately sampled another subset of control subjects that were matched for IQ to understand whether any potential differences were due to differences in IQ across our initial age-matched groups (Table 2).

[TABLE 1 HERE]

Stimuli

Stimuli were nonspeech static ripples varying in temporal and spectral modulation previously validated in prior research on category learning in both children and adults (Gabay et al., 2023; Reetzke et al., 2016; Roark et al., 2021, 2023; Roark & Chandrasekaran, 2023; Yi & Chandrasekaran, 2016). These pairs of dimensions are fundamental aspects to natural sounds including speech (Woolley et al., 2005) and prior work has examined perception and learning within these ranges of temporal (2-15 Hz) and spectral modulation (-0.38-2.67 cyc/oct; Roark et al., 2021, 2023; Roark & Chandrasekaran, 2023; Schönwiesner & Zatorre, 2009; Woolley et al., 2005). Prior work has demonstrated that both children and adults can selectively attend to temporal modulation (Roark et al., 2021; Roark et al., 2023) and map relative differences along temporal modulation onto clear verbal labels (e.g., “fast” and “slow”). As such, listeners can map changes on this dimension to unidimensional rules.

Arbitrary categories were defined to match either rule-based (RB) categories (Figure 1A) or information-integration (II) categories (Figure 1B). A single category for the RB categories was first created using bivariate Gaussian sampling, with 100 stimuli. Gaussian sampling was used to create some noise in the category distributions, as is observed with natural categories (Ashby & Gott, 1988; Liberman et al., 1967; Nosofsky et al., 2018; Swingley, 2005). The other category was created by mirroring that category across the stimulus space. The II categories were created by rotating the RB categories by 45 degrees. As a result, each of the individual categories have the same stimulus distributions. Additionally, due to the sampling, there was very slight overlap between the two categories within a distribution, which makes category membership somewhat probabilistic, which can positively affect II learning without affecting RB learning (Ell & Ashby, 2006).

The RB categories require selective attention to the temporal modulation dimension and the II categories require integration across both temporal and spectral modulation dimensions. In contrast to prior work in adults with dyslexia (Gabay et al., 2023), we chose to train children on two categories instead of four categories to increase the likelihood that they would learn.

[FIGURE 1 HERE]

Procedure

After an initial assessment session, all included participants learned both the RB and II categories in separate tasks, with the order counterbalanced across participants. The category learning tasks were very similar. The trial procedure was identical with the only difference being the objects present on the screen. Participants were given a cover task about traveling to different planets and listening to different aliens talk as they decide who was talking. Across RB and II category tasks, there were different sets of aliens and different planets in the instructions to further prevent carryover effects.

On each trial, participants heard a 1 sec sound followed immediately by a prompt on the screen of “Who was talking?” with pictures of the two aliens and their associated keypress responses (i.e., “1”, “2”). Assignment of sound category-to-alien and motor response were counterbalanced across participants. Participants made an untimed response about the category identity which was followed immediately by corrective feedback (smiling face for correct, neutral face for incorrect) for 1 sec and a 1 sec ITI. Participants were given explicit instructions at the beginning of the task about how to interpret the smiling and neutral faces. Participants were not given any instructions about the dimensions that defined the categories.

In both category tasks, there were 50 trials in each of four blocks. Participants encountered each stimulus exactly once (100 stimuli * 2 categories = 200 stimuli). To maintain motivation, after each block, participants uncovered another piece of a puzzle that was completely revealed at the end of the task. There was a separate puzzle for the two tasks. After the four training blocks, participants completed 64 trials of a generalization task wherein they categorized novel stimuli drawn from an 8x8 grid (Figure 1 - Xs). Participants did not receive any feedback during the generalization task.

The primary outcome measure was accuracy in category learning, and we were particularly interested in the potential interaction between group (Dyslexia, Control) and category type (II, RB). A power analysis indicated that with samples of 25 children in each group, with an alpha of 0.05 and power of 0.90, we would be able to detect a large interaction effect ($f = 0.48$).

Decision Bound Models

Decision bound models (Ashby & Gott, 1988; Ashby & Maddox, 1992) were fit to each block of each participant's data to estimate their learning strategy. We fit several versions of models within three different classes – rule-based, integration, and exploration/guessing.

The rule-based models assumed that participants used a single dimension (e.g., unidimensional rule) to separate the stimuli into categories. We fit separate versions of these models that assume participants use either the temporal modulation dimension or spectral modulation dimension and versions that assumed different assignments of responses to regions of the stimulus space (e.g., category A on the left, category B on the right or vice versa). A rule-based strategy along the temporal modulation dimension is optimal for the RB categories. The rule-based models have two free parameters – one for placement of the decision boundary along the relevant dimension and one for perceptual and criterial noise.

The integration model assumed that participants used both dimensions (e.g., a linear, diagonal boundary) to separate the stimuli into categories. We fit separate versions of the integration model that assumed different assignments of responses to regions of the stimulus space. An integration strategy with a positive slope is optimal for the II categories. The integration models have three free parameters – one for the slope of the boundary, one for the intercept of the boundary, and one for perceptual and criterial noise.

The exploration/guessing models assumed that participants guessed the category identity. This type of model would also be the best-fit model if participants were not clearly using rule-based or integration strategies. As a result, we interpret usage of this 'strategy' as consistent with either exploration of several kinds of strategies not captured by these models or random guessing. We fit three versions of exploration/guessing models – two versions assumed that participants had biased responses towards one category or the other and one version assumed that participants balanced their responses across categories. The exploration/guessing models have one free parameter –the probability of responding one category (for which the probability of responding the other category is 1 minus that probability).

Each version of each model class was fit to each block of responses for all participants. Models were fit using maximum likelihood procedures (Wickens, 1982) and the best-fitting model was selected based on the Bayesian Information Criterion (BIC; Schwarz, 1978), where $BIC = r\ln N - 2\ln L$, where r is the number of free parameters, N is the number of trials in a given block for a given subject, and L is the likelihood of the model given the data. The model with the lowest BIC value was selected as the model that best-fit the participant's responses for that given block.

We conducted model recovery simulation analyses to ensure that the models could accurately detect the type of strategy they were designed to detect (Edmunds et al., 2018). We simulated response data for each of the strategies (unidimensional rule along temporal modulation, unidimensional rule along spectral modulation, integration, and exploration/ guessing) 10 times for each category (total of 80 simulated datasets, 40 for each category). We applied a deterministic response strategy for the simulated parameters, with the ranges of the parameters based on reasonable ranges of the category distributions. We compared the best-fit model to the true simulated model. Overall, these simulations demonstrated that the models can accurately detect participant strategies – 100% of RB category models and 98% of II category models identified the correct simulated strategy. As additional evidence of good fit, the models accurately estimated the ground-truth simulated parameters of the estimated data ($r = .996$). We also examined the ability of the best-fit model to accurately capture the variability in participants' responses. There was a model prediction accuracy of 70% for the II categories and 72% for the RB categories. This indicates that the models can capture variability in responses better than chance (50%) and that the best-fit strategies can accurately account for participants' patterns of responses.

Results

Category Learning Performance

We compared learning performance in typically developing children and children with dyslexia using a mixed model ANOVA with group (Dyslexia, Control), category (RB, II) and block (1-4) as factors. Children with dyslexia had significantly worse performance than typically-developing controls, collapsing across categories (Figure 2A; $F(1, 48) = 4.54$, $p = .038$, $\eta_G^2 = 0.032$; Control: $M = 60\%$, Dyslexia: $M = 56\%$). No other main effects or interactions were statistically significant (*F*s < 2.40, *p*s > .12) indicating that category learning performance accuracy did not significantly differ across RB and II categories or across blocks.

Relevant to our contrasting predictions, we did not find a significant interaction between group and category type ($F(1, 48) = 2.40$, $p = .13$, $\eta_G^2 = 0.011$). However, it is important to note that unless the interaction effect was large ($f = 0.48$), we would not have enough power to detect it given our sample size. To better contextualize these results, we conducted exploratory post-hoc analyses to compare the groups separately for RB and II categories. For RB categories, children with dyslexia performed significantly worse than controls (Control: $M = 61\%$, $SD = 10.1$; Dyslexia: $M = 55\%$, $SD = 7.00$; $t(42.8) = 2.53$, $p = .015$, $d = 0.72$), but for II categories, there were no significant differences in performance across groups (Control: $M = 58\%$, $SD = 8.51$; Dyslexia: $M = 56\%$, $SD = 7.35$; $t(47.0) = 0.74$, $p = .46$, $d = 0.21$).

Despite the relatively flat performance across blocks, participants in both groups demonstrated evidence of learning as performance was significantly above chance levels (one-sample *t*-tests compared to 50%) of performance in both RB and II tasks (Dyslexia-RB: $M = 55\%$; Dyslexia-II: $M = 56\%$; Control-RB: $M = 61\%$; Control-II: $M = 58\%$; *p*s < .0001). The flat performance across blocks indicates that most learning occurred within the first 50 trials. While many children struggled to learn, some children learned quite well (maximum accuracy: Dyslexia-RB = 76%; Dyslexia-II = 86%; Control-RB = 88%; Control-II = 88%). There was limited evidence for carryover effects across tasks (see Supplementary Materials).

[FIGURE 2 HERE]

Learning Strategies

Children with dyslexia and controls used similar strategies across the two tasks (Figure 3A). Among all participants, there were no significant differences in learning strategies between children with dyslexia and controls in any block during RB (Fisher's exact tests, $ps > .20$) or II learning (Fisher's exact tests, $ps > .14$). Most participants in both groups used exploration/guessing strategies (final block: II-Dyslexia: 60%, II-Control: 50%, RB-Dyslexia: 68%, RB-Control: 58%). This type of strategy could reflect random guessing or indicate that participants are switching between different types of strategies very frequently during learning such that their strategy could not be captured well by any of the other models. A smaller subset of participants used unidimensional rule-based strategies (the temporal rule strategy is optimal for RB categories), with very few using integration strategies (the integration strategy is optimal for II categories).

[FIGURE 3 HERE]

We also examined whether children with dyslexia differed from controls in how quickly participants used the optimal strategy (Figure 3B), how many total blocks participants used the optimal strategy (Figure 3C), and among those participants using the optimal strategy in the final training block, how accurately they applied this strategy (Figure 3D). As a supplementary analysis, we compared the precision of strategies in the final training block by comparing placement of the decision boundaries in the two-dimensional space (see Supplementary Materials). We compared the first two measures using mixed model ANOVAs with category as a within-subjects factor and group as a between-subjects factor. We compared groups' accuracy for those using the optimal strategies in the final block. Because no children with dyslexia used the optimal procedural strategy in the final block of II learning, we only compare performance across groups during RB learning using a *t*-test.

First Optimal Block

We determined the first block that participants used the task-optimal strategy when learning the two types of categories. If participants never used the optimal strategy for a category, we assigned the value of 5, indicating that they never applied the optimal strategy during the four training blocks. Participants in both groups were significantly faster to use the optimal temporal rule strategy during RB learning compared to the integration strategy during II learning ($F(1, 48) = 10.3$, $p = .002$, $\eta_G^2 = 0.091$). Participants used the optimal strategy in 3.38 ($SD = 1.72$) blocks on average when learning RB categories compared to 4.32 ($SD = 1.32$) blocks when learning II categories. Children with dyslexia ($M = 4.16$ blocks, $SD = 1.45$) took marginally more blocks to use the optimal strategy for either category type compared to controls ($M = 3.54$ blocks, $SD = 1.69$) though this was not statistically significant ($F(1, 48) = 3.96$, $p = .052$, $\eta_G^2 = 0.042$). There was no significant interaction between category type and group ($F(1, 48) = 0.56$, $p = .46$, $\eta_G^2 = 0.005$).

Total Optimal Blocks

We determined the total number of blocks that participants used the optimal strategy in the two tasks. We found that participants used the optimal strategy significantly more during RB learning ($M = 1.16$ blocks, $SD = 0.20$) than II learning ($M = 0.30$ blocks, $SD = 0.082$; $F(1, 48) = 18.4$, $p < .0001$, $\eta_G^2 = 0.15$). Children with dyslexia ($M = 0.50$ blocks, $SD = 0.14$) used the optimal strategy in significantly fewer blocks than controls ($M = 0.96$ blocks, $SD = 0.18$; $F(1, 48) = 4.31$, $p = .043$, $\eta_G^2 = 0.047$). There was no significant interaction between category type and group ($F(1, 48) = 0.81$, $p = .37$, $\eta_G^2 = 0.008$).

Efficiency of Optimal Strategies

We determined the efficiency of participants' optimal strategy use by isolating those participants who used the optimal strategy in the final block of each category type and then compared accuracies across groups. No children with dyslexia and only three control participants used the optimal strategy in the final block of II learning. Because no children with dyslexia used the optimal strategy during II learning, we only compared performance during RB learning (Dyslexia: N = 6; Control: N = 10). We found that during RB learning, participants using the optimal strategy in the two groups did not have significantly different accuracies ($t(10.3) = 0.31$, $p = .76$, $d = 0.14$).

In post-hoc analyses, considering only individuals who used the optimal strategy in the final block, we examined whether the groups differed in their use of strategies across the other blocks. There were no significant differences between children with dyslexia and controls in the first optimal block ($t(11.1) = 0.60$, $p = .56$, $d = 0.31$) or total optimal blocks ($t(10.4) = 0.056$, $p = .96$, $d = 0.029$). Only six children with dyslexia and 10 controls used the task-optimal strategy in the final block of RB learning. Thus, we encourage caution in interpreting these results. However, this could indicate that if children with dyslexia are able to find optimal rules, they may perform similarly to typically developing children.

We also examined whether children with dyslexia who used the optimal RB strategy had differences in reading scores compared to children with dyslexia who used suboptimal strategies during RB learning. There were no significant differences in reading scores (Word Attack: $t(17.2) = -0.41$, $p = .68$, $d = -0.16$; Word ID: $t(13.1) = -0.50$, $p = .62$, $d = -0.21$; Phonemic Decoding Efficiency: $t(10.8) = 1.21$, $p = .25$, $d = 0.53$; Sight Word Efficiency: $t(8.07) = 0.17$, $p = .87$, $d = 0.082$) among children with dyslexia who used the optimal strategy and those who used the suboptimal strategy. This indicates that while some children with dyslexia may be able to find optimal rules to perform well in this category learning task, it does not appear to reflect differences in reading abilities from children who are unable to find optimal rules.

Generalization Test

Finally, we examined participants' ability to generalize their learned category knowledge to novel exemplars drawn from a grid of stimuli across the entire stimulus space. Participants did not receive feedback in the generalization test. We computed accuracy in the generalization test by first removing stimuli that fell directly along the category boundary and thus did not have a correct response.

On average, participants were able to successfully generalize their category knowledge in the generalization test with performance in all cases significantly above chance levels (one-sample t-tests vs. 50% chance; ps < .019; II-Dyslexia: M = 56%, II-Control: 61%, RB-Dyslexia: 59%, RB-Control: 62%). When comparing generalization test accuracy in the test block relative to the final block (Figure 4A), participants seamlessly transferred their knowledge, with overall no significant loss in performance in the generalization test (one-sample t-tests versus 0; ps > .23). There were no significant differences in generalization transfer between category types ($F(1, 48) = 0.26$, $p = .61$, $\eta_G^2 = 0.002$), groups ($F(1, 48) = 0.42$, $p = .52$, $\eta_G^2 = 0.005$), and no significant interaction between category type and group ($F(1, 48) = 0.20$, $p = .66$, $\eta_G^2 = 0.002$).

[FIGURE 4 HERE]

As during training, there were no significant differences in the types of strategies participants used in the test block (Figure 4B) for either RB (p = .19) or II categories (p = .66). While many participants used exploration/guessing strategies during the test (Dyslexia-II: 52%; Control-II: 52%; Dyslexia-RB: 60%; Control-RB: 40%), participants also often used the temporal rule strategy (Dyslexia-II: 40%; Control-II: 32%; Dyslexia-RB: 28%; Control-RB: 52%). Whereas 7/25 (28%) children with dyslexia and 13/25 (52%) controls used the optimal temporal rule strategy in the RB test, only 2/25 (8%) children with dyslexia and 2/25 (8%) controls used the optimal integration strategy in the II test.

As before, we compared the accuracies of participants in the two groups who used the optimal strategies (Figure 4C). Though overall there were relatively few participants using the optimal strategy during II learning (2 Dyslexia, 2 Control), among those using the optimal strategy, there were no significant differences across groups ($t(1.22) = 2.53$, $p = .20$, $d = 2.53$). While more participants used the optimal strategy during RB learning (7 Dyslexia, 13 Control), among those using the optimal strategy, there were also no significant differences across groups ($t(12.3) = 0.32$, $p = .76$, $d = 0.15$). When learners with dyslexia can find and use the optimal rule-based strategy, they appear to do so just as effectively as controls. Due to the relatively smaller number of subjects using the optimal strategies, especially during II learning, we encourage caution when interpreting these results.

Potential Sources of Learning Difficulties

It is important to note that many children in this study in both groups had difficulty learning these categories. As a supplementary analysis, we examined potential sources of this difficulty to better understand what enabled some children to learn, while others struggled. Our approach involved examining the correlations between final block accuracy for II and RB categories and age, reading ability, and nonverbal IQ measures (see Supplementary Materials for full analysis). Given the exploratory nature of these analyses and the difficulty in learning across children in both groups, we decided to examine all participants together for this analysis, rather than separately across groups.

Overall, no measures were significantly related to II learning outcomes (rs < 0.23, ps > .11) and no measures except for Phonemic Decoding Efficiency were significantly related to RB learning outcomes (rs < 0.28, ps > .059). Phonemic Decoding Efficiency was significantly positively related to RB learning outcomes ($r = 0.32$, $p = .023$), indicating that across all children, the better able they were to quickly decode pronounceable non-words the better they are able to learn categories that require sound-to-rule mapping. Together, these results indicate that whether children learned RB or II categories was not clearly related to their age, nonverbal IQ, or most reading scores and, instead, children may have struggled to learn for a variety of other reasons. The ability to learn RB, but not II categories, was moderately related to Phonemic Decoding Efficiency, suggesting that poor phonological awareness may relate to the general ability to learn sound-to-rule mappings, which could possibly then underlie the difficulty in learning sound-to-letter mappings in dyslexia.

Nonverbal IQ Matched Groups

Because our age-matched sample of control participants had significantly higher nonverbal IQ scores than the participants with dyslexia, we conducted additional analyses with a separate selection of control participants that were matched for nonverbal IQ (11 Males, 9 Females). In this sample, children with dyslexia had significantly lower scores on Word Attack ($p < .0001$), Word ID ($p < .0001$), Phonemic Decoding Efficiency ($p < .0001$), and Sight Word Efficiency ($p < .0001$) measures compared with controls but did not differ on age ($p = .36$) or nonverbal IQ scores ($p = .41$).

[TABLE 2 HERE]

For simplicity, we briefly summarize the results here and include full details in the Supplementary Materials. Results with the IQ-matched control group were very similar to results with the age-matched control group. The key result of the marginal interaction between group and task in category learning performance was found in both datasets. Follow up analyses indicated that children with dyslexia performed marginally worse than controls in learning RB categories but did not significantly differ in learning II categories. As such, even when accounting for incidental differences in nonverbal IQ, children with dyslexia may demonstrate RB-specific learning challenges, with no clear differences in II learning performance.

Discussion

Research on developmental dyslexia suggests a selective deficit in procedural learning and memory, with intact declarative learning and memory (Lum et al., 2013; Nicolson et al., 2010; Nicolson & Fawcett, 2007; Ullman, 2004; Ullman et al., 2017; West, Clayton, et al., 2019; West, Vadillo, et al., 2019). We examined auditory category learning in children with dyslexia and typically developing controls, with categories argued to be dependent on procedural or declarative learning mechanisms. In contrast to findings with adults which support a specific II category learning deficit (Gabay et al., 2023; Sperling et al., 2004), our results are generally consistent with an interaction of the effects of dyslexia on learning with the development of category learning. Children with dyslexia demonstrated a general deficit in *both* RB and II category learning, though this may have been due to incidental differences in nonverbal IQ abilities across age-matched groups. We found preliminary evidence for an especially pronounced deficit in RB learning in children with dyslexia coupled with difficulty in finding optimal strategies relative to typically developing children. These results suggest that developmental dyslexia impacts category learning differently across development. While 7-12-year-old children have general learning difficulties and a potentially selective deficit in RB learning, adults may find compensatory mechanisms over the course of development that preserve RB learning, while developing difficulties in II learning.

Developmental Trajectory of Learning in Dyslexia

While adults with dyslexia demonstrate a selective impairment in II learning and procedural strategy use (Gabay et al., 2023; Sperling et al., 2004), children with dyslexia in the current study had the clearest impairments in RB learning. Additionally, while many children in both groups struggled to find task-optimal strategies, children with dyslexia seemed to struggle even more than typically developing children – it took the dyslexia group marginally more blocks to use optimal strategies and they used the optimal strategies in significantly fewer blocks. This pattern diverges from what has been seen in adults where the deficit is limited to procedural strategy use. Interestingly, mirroring the results in adults, when children with dyslexia used the optimal rule-based strategy in training or test, they did not perform significantly differently from controls. This may indicate that as long as individuals with dyslexia have access to a successful rule-based strategy, they can perform just as well as controls, with substantial individual differences in both groups. What may change over the course of development is that adults have more consistent access to compensatory strategies, potentially supported by the development of selective attention mechanisms.

While we observed some RB learning deficit in 7-12-year-old children with dyslexia, there were no RB learning differences in adults with dyslexia in Gabay et al. (2023). It would be useful for future work to examine the developmental trajectory of category learning in dyslexia across a longer continuum to identify at which point individuals with dyslexia consistently develop compensatory strategies that preserve RB learning but become impaired in II learning.

Learning Strategies in Children

Many children in the current study persisted with exploratory/guessing strategies. This is in line with prior work where children tend to perseverate with suboptimal rule-based strategies in II tasks or use exploratory/guessing strategies during RB and II learning (Miles et al., 2014; Rabi & Minda, 2014; Reetzke et al., 2016; Roark et al., 2023; Roark & Holt, 2019). Children tend to solve problems differently from adults (Blanco et al., 2023; Blanco & Sloutsky, 2019, 2021b; Cohen et al., 2023; Liquin & Gopnik, 2022; Rabi & Minda, 2014; Roark et al., 2023; Roark & Holt, 2019). Specifically, due to development of selective attention mechanisms, whereas adults are likely to selectively attend to task-relevant features to optimize performance, children distribute their attention across multiple features, even when they are not necessarily relevant for the task (Blanco & Sloutsky, 2021a; Deng & Sloutsky, 2016; Plebanek & Sloutsky, 2017; Sloutsky & Fisher, 2004, 2011). This pattern of attention has obvious negative consequences for RB learning, where performance is impaired if children do not selectively attend to the relevant dimension (Reetzke et al., 2016; Roark et al., 2023), but can be helpful in other contexts, such as remembering information that was task-irrelevant (Sloutsky & Fisher, 2004) or switching attention when previously irrelevant information becomes relevant (Blanco & Sloutsky, 2021a).

Even though most adults can find optimal strategies in tasks like these (Roark et al., 2021; Roark & Chandrasekaran, 2023), not all learners find optimal strategies. Some learners (whether children or adults) may perform moderately well with a suboptimal or exploratory strategy. As such, while we explored strategies in depth when participants use the optimal strategy, it is still informative that children with and without dyslexia primarily use exploratory/guessing strategies during these tasks. Future work should examine possible manipulations to help children find optimal strategies and whether these manipulations may be more or less effective in typically developing children compared to children with dyslexia.

Limitations

We conducted these auditory learning experiments with children online. While recent research has demonstrated that in-person findings of auditory learning and perception generally replicate in online conditions (Mok et al., 2023; Roark et al., 2021, 2022; Zhao et al., 2022), this has not yet been tested in children. It is possible that children are much more susceptible than adults to distractions or other technological challenges posed by an online environment. Though overall learning performance ranges differed across individuals in the current study, many individuals struggled to learn. At least some of these learning difficulties may have been due to learning in an online environment in the child's home. However, it is important to note that the learning performance observed here is comparable to prior studies of auditory learning where children and experimenters were physically in the room together (Huang-Pollock et al., 2011; Reetzke et al., 2016; Roark & Holt, 2019). Future work should focus on validating auditory perception and learning methods in online environments in children and directly test whether the current results replicate in groups of children tested in in-person contexts.

We are somewhat limited here in explaining the source of learning difficulties in these groups of children. Learning outcomes were not significantly related to age, most reading scores, or nonverbal IQ scores. We did not measure children's environments during learning (e.g., presence of others, presence of distractors, etc.). While we can only speculate about the role of the learning environment on learning outcomes, it is important to acknowledge that presence of distractors and even visual complexity impairs learning in classroom environments (Fisher et al., 2014; Godwin et al., 2022) and book reading contexts (Eng et al., 2020). Future research should directly measure the impact on room environmental complexity and distraction on category learning in children in online environments.

Finally, we were limited in our statistical power to observe a small or moderate size interaction between group (Dyslexia, Control) and category type (RB, II) on learning outcomes. Based on our sample size of 25 participants in each group, we had sufficient power to detect a large interaction between these variables. While we did not observe a statistically significant interaction and the observed interaction effect size was small, subsequent exploratory analyses revealed different effects of group depending on the task. Specifically, while children with dyslexia did not perform significantly differently from controls when learning II categories, they performed significantly worse when learning RB categories. We stress the importance of not overinterpreting these separate results given the lack of a significant interaction. However, future work can better tease apart the potential interaction with a higher-powered sample. As this is the first study to examine RB and II category learning in children with dyslexia, it provides the groundwork for future studies to explore this question in greater depth.

Theoretical Implications

These results have important implications for our theoretical understanding of dyslexia and particularly demonstrate that dyslexia affects auditory category learning differently in children and adults. Auditory category learning involves mapping sounds to category labels either by mapping sound-to-rule (RB) via declarative rule-based processes or sound-to-response (II) via associative or procedural learning processes. As such, comparing RB and II category learning can adjudicate between conflicting theoretical hypotheses that suggest either general auditory processing deficits (e.g., Share, 2021; Stanovich, 1988; Tallal, 1980; Zoccolotti, 2022) or specific procedural learning deficits in dyslexia (e.g., Lum et al., 2013; Nicolson et al., 2010; Nicolson & Fawcett, 2007; Ullman, 2004; Ullman et al., 2017).

Overall, we found that children have distinctly different patterns from adults who demonstrate specific procedural learning deficits (II learning is impaired, RB learning is unaffected; Gabay et al., 2023; Sperling et al., 2004). Though we failed to observe a significant interaction between group and category type, exploratory post-hoc analyses suggested that if children with dyslexia have learning differences from typically developing children, RB learning may be more impacted than II learning. This is the opposite pattern than what has previously been found in adults.

As such, our results do not provide support for the Procedural Deficit Hypothesis in auditory category learning in children with dyslexia. Instead, our results suggest that development of cognitive abilities that impact general learning abilities interact with the effects of dyslexia. Additional work is needed to identify the developmental trajectory of RB and II category learning abilities (preferably in the same individuals over time) and how this relates to reading abilities.

Conclusion

In all, we found that children with dyslexia do not demonstrate the same selective deficits in category learning as adults with dyslexia. While adults with dyslexia are selectively impaired at finding procedural strategies and learning II categories, children with dyslexia have especially pronounced in difficulties finding rule strategies and learning RB categories. These results suggest that auditory category learning is impacted in dyslexia *and* across development and that as they age, individuals with dyslexia may develop compensatory strategies that enables a preservation of rule-based learning.

Author Contributions

C.L.R, B.C., and T.M.C. conceptualized the study. C.L.R. designed the study. V.T. coordinated data collection. V.T. and C.L.R. pre-processed the data. C.L.R. conducted formal analysis of the data, conducted computational modeling, and visualized the data. C.L.R. wrote the original draft and V.T., B.C., and T.M.C. provided review and editing comments. B.C. and T.M.C. acquired financial support for the study.

Conflicts of Interest

The authors have no conflicts of interest to report.

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Data Availability Statement

Stimuli and data are publicly accessible through the Open Science Framework at https://doi.org/10.17605/OSF.IO/BH62T.

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Tables and Figures

Table 1

Demographics and Reading Scores for Age-Matched Groups

Measure	Control (n = 25)	Dyslexia (n = 25)	t value (p value)
Age	10.0 (1.38)	10.1 (1.48)	-0.27 (.79)
KBIT (Nonverbal IQ)	115.9 (11.3)	106.3 (11.4)	3.00 (.0042)
Word Attack Standard Score	110.0 (10.7)	87.8 (10.0)	7.59 (< .0001)
Word ID Standard Score	116.8 (10.8)	87.5 (11.3)	9.37 (< .0001)
TOWRE-2 Phonemic Decoding Efficiency Standard Score	107.2 (13.1)	77.9 (8.21)	9.46 (< .0001)
TOWRE-2 Sight Word Efficiency Standard Score	106.9 (15.7)	79.6 (6.79)	8.02 (< .0001)

Table 2

Demographics and Reading Scores for Nonverbal IQ-Matched Groups

Measure	Control (n = 25)	Dyslexia (n = 25)	t value (p value)
Age	9.70 (1.34)	10.1 (1.48)	-0.93 (.36)
KBIT (Nonverbal IQ)	108.9 (10.9)	106.3 (11.4)	0.84 (.41)
Word Attack Standard Score	109.2 (12.1)	87.8 (10.0)	6.83 (< .0001)
Word ID Standard Score	114.4 (11.1)	87.5 (11.3)	8.53 (< .0001)
TOWRE-2 Phonemic Decoding Efficiency Standard Score	107.4 (13.5)	77.9 (8.21)	9.29 (< .0001)
TOWRE-2 Sight Word Efficiency Standard Score	107.3 (16.0)	79.6 (6.79)	8.00 (< .0001)

Figure 1

Category Distributions

Note. Category distributions for A. Rule-Based (RB) and B. Information-Integration (II) categories. Category stimuli are shown in different colors. Generalization stimuli are shown as black Xs. Black lines reflect optimal decision boundaries.

Figure 2

Category Learning Accuracy

Note. Error bars reflect *SEM.* A. Average accuracy across groups, tasks, and blocks. B. Average accuracy across groups to demonstrate the significant main effect of group. No other main effect (block, task) or interaction was significant.

Figure 3

Strategies during Category Learning

Note. Error bars reflect *SEM.* A. Proportion of participants using different strategies across category learning blocks. B. Average number of first block participants used the task-optimal strategy (II: Integration; RB: Temporal Rule). If participants never used the optimal strategy, they were given a value of 5. C. Average number of total optimal blocks participants used the task-optimal strategy. If participants never used the optimal strategy, they were given the value of 0. D. Proportion correct for participants using the task-optimal strategy in the final block of each task. No children with dyslexia used the II-optimal Integration strategy in the final block of the II task.

Figure 4

Performance and Strategies in the Generalization Test

Note. Error bars reflect *SEM.* A. Transfer of categorization performance from training to generalization test without feedback and with new stimuli across a grid. Accuracy was calculated by first removing any stimuli that fell directly between the categories (e.g., along the optimal boundary between categories). B. Proportion of participants using different strategies in generalization test. C. Proportion correct for participants using the task-optimal strategy in the generalization test.