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Differential Effects of Cognitive Load on Working Memory in Students with Linguistic Versus Perceptual Dyslexia

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A B S T R A C T

Children with dyslexia do not demonstrate homogeneous neuropsychological characteristics. The present study aimed to compare verbal working memory performance under different levels of cognitive load between two primary dyslexia subgroups, namely perceptual and linguistic types. In this comparative research design, 35 Persian-speaking children aged 7 to 10 years were selected through purposive sampling. Diagnostic and subgroup classification procedures were conducted based on the criteria of the Diagnostic and Statistical Manual of Mental Disorders (DSM-5), the Reading Test (Pour-Etemad & Jahani, 2001), Raven's Colored Progressive Matrices, the Conners Parent Rating Scale, and the application of Baker's balance model framework. The primary assessment instrument was a computerized verbal N-Back task. The collected data were analyzed using multivariate analysis of variance (MANOVA). The findings indicated a significant interaction between subgroup type and cognitive load level. Although the performance of the two groups was similar at lower task demands (1-Back and 2-Back conditions), a clear differentiation emerged under high cognitive load conditions (2-Back), such that the accuracy of the perceptual subgroup was significantly higher than that of the linguistic subgroup. These results suggest that verbal working memory deficits in dyslexia are neither global nor stable; rather, they follow a cognitive load–dependent pattern specific to the linguistic subtype. The evidence provides compelling support for the existence of distinct cognitive architectures and underscores the necessity of designing targeted and individualized intervention programs.

Keywords: *Working memory, linguistic dyslexia, perceptual dyslexia, N-Back task, cognitive load.*

1. Introduction

Developmental dyslexia is among the most prevalent neurodevelopmental learning disorders and is characterized by persistent difficulties in accurate and/or fluent word recognition, decoding, and spelling despite adequate instruction and intelligence. Contemporary diagnostic frameworks emphasize that these difficulties are not better explained by sensory impairment, neurological disease, or broader intellectual disability, and they frequently co-occur with other developmental conditions. In the *Diagnostic and Statistical Manual of Mental Disorders* (DSM-5), dyslexia is typically conceptualized within Specific Learning Disorder with impairment in reading, highlighting both the developmental course and functional consequences for academic achievement and psychosocial adjustment. (American Psychiatric, 2013) Importantly, dyslexia is not a unitary condition; rather, accumulating evidence suggests substantial heterogeneity in cognitive profiles, neurobiological correlates, and response to intervention. This heterogeneity is increasingly salient in contexts where early screening and targeted intervention are public health priorities, including Iran, where recent syntheses indicate non-trivial prevalence estimates among primary school children and underscore the need for mechanisms-based assessment frameworks that can guide personalized support. (Sakhai et al., 2025)

A central implication of dyslexia heterogeneity is that different children may show distinct constellations of impairments—phonological, orthographic, attentional, executive, or multimodal—each with partially separable developmental trajectories. Multifactorial accounts have therefore gained traction because single-deficit theories cannot adequately explain the breadth of behavioral patterns and neurocognitive findings. (Lorusso & Toraldo, 2023; O'Brien & Yeatman, 2021) In parallel, computational and personalized modeling approaches have been proposed as an avenue for bridging theory to practice by formalizing individual differences and generating intervention-relevant predictions. (Ziegler et al., 2020) Within this broader shift, the question is no longer whether dyslexia involves phonological deficits, visual-attentional anomalies, or executive dysfunction, but rather how these components interact under varying task demands and how subgroups can be meaningfully identified in ways that map onto mechanisms and treatment selection. (Lorusso & Toraldo, 2023; O'Brien & Yeatman, 2021)

One influential strand of subgroup research distinguishes "accuracy-disability" and "rate-disability" (or "accuracy vs. rate") profiles, which has been validated in alphabetic scripts beyond English and has direct implications for how reading problems are operationalized. Evidence from Arabic reading has supported the validity of accuracy- versus rate-based subtypes, suggesting that different error patterns and speed–accuracy trade-offs may reflect partially distinct underlying constraints. (Shany et al., 2023) Extending this line, recent work on Arabic-speaking university students has further contributed to reading subtyping within the accuracy–rate model, strengthening the argument that subtyping captures stable individual differences rather than purely task artifacts or educational history. (Tarabya et al., 2025) In other orthographies and populations, researchers have also proposed subtyping grounded in phonological and visual parameters, reinforcing the idea that subgroups can be characterized along dimensions that plausibly correspond to differential cognitive architectures. (Germano & Capellini, 2025) These findings resonate with long-standing clinical perspectives that "type of treatment matters," because interventions targeting phonological decoding may not be optimal for learners whose primary bottleneck lies in visual-attentional allocation or rapid serial processing constraints. (Lorusso et al., 2011)

Working memory (WM) is a particularly promising domain for examining mechanisms that may differentiate dyslexia subgroups, because WM supports the temporary maintenance and manipulation of information required for decoding, grapheme–phoneme integration, lexical access, and comprehension monitoring. (Baddeley, 2017; Cowan, 2012) Meta-analytic evidence indicates a robust association between reading and WM, suggesting that WM capacity and efficiency are systematically linked to reading development and reading difficulties. (Peng et al., 2018) Longitudinal research further suggests that early WM abilities can predict later reading outcomes, which implies that WM is not merely a downstream consequence of poor reading experience but may be part of the developmental causal chain for some learners. (Nevo & Bar-Kochva, 2015) At the same time, WM is not monolithic: verbal WM, visuo-spatial WM, and executive control components may be differentially implicated depending on the learner's profile and on the cognitive load imposed by a given task. (Cowan, 2012; Logie, 2014) From this perspective, subgroup differences may emerge most clearly under conditions that tax control, updating, and interference management—functions typically associated with the central executive and broader executive functioning systems. (Alt et al., 2022; Lonergan et al., 2019; Maehler & Schuchardt, 2016)

Empirical studies of WM in dyslexia increasingly show profile-specific patterns rather than uniform deficits. For example, WM profiles differ across children with dyslexia, developmental language disorder, and comorbidity, implying that WM measures can help dissociate overlapping learning phenotypes and reduce diagnostic ambiguity. (Gray et al., 2019) Similarly, evidence suggests that phonological working memory and central executive function can be dissociated in children with typical development versus dyslexia, highlighting that the locus of difficulty may vary between storage-limited and control-limited constraints. (Alt et al., 2022) WM differences are also relevant for higher-order reading outcomes: WM capacity has been linked to text comprehension performance in children with dyslexia and dyscalculia, supporting the notion that WM limitations can propagate from word-level processing to discourse-level integration. (López-Resa & Moraleda-Sepúlveda, 2023) Taken together, these findings motivate analyses that do not treat WM impairment as a single trait but instead examine how WM performance changes as cognitive load increases and as task demands shift from simple maintenance to active updating and interference control.

The N-back paradigm is widely used to operationalize WM updating and load-dependent control, making it suitable for probing whether subgroup differences become more pronounced under higher cognitive load. Large-scale neuroimaging syntheses have mapped normative neural activation patterns in N-back tasks, demonstrating reliable engagement of fronto-parietal systems and providing a benchmark for interpreting atypical patterns. (Owen et al., 2005; Rottschy et al., 2012) Importantly, task characteristics matter: stimulus modality, presentation format, and load level can elicit distinct brain activity patterns, indicating that behavioral differences across groups may reflect both individual capacity and the specific constraints induced by stimuli and timing. (Leopold et al., 2024; Mencarelli et al., 2019) At the neural level, different verbal WM tasks can rely on partially dissociable lesion–symptom mappings, reinforcing the need to specify the cognitive operations being sampled by a given WM measure rather than treating "verbal WM" as a uniform construct. (Ivanova et al., 2018) In dyslexia specifically, both behavioral and neurophysiological work points to WM-related vulnerabilities, with evidence for working memory impairment in children with dyslexia and corresponding neurophysiological differences that may be amplified under high task demands. (Wang et al., 2022)

In parallel with WM-focused accounts, a large body of research highlights sensory-attentional mechanisms that can intersect with WM during reading. Visual-spatial attention has been shown, meta-analytically, to play a role in reading development, suggesting that attention allocation and scanning efficiency may constrain the rate and stability of letter/word processing. (Gavril et al., 2021) This aligns with magnocellular and visual-attention perspectives that emphasize temporal sampling, attentional gating, and oscillatory dynamics as potential contributors to dyslexic reading difficulties, particularly those related to reading speed and serial processing. (Stein, 2019; Vidyasagar, 2019) Auditory temporal processing also appears relevant: adults with dyslexia have been shown to be impaired in categorizing speech and nonspeech sounds based on temporal cues, a deficit that could affect phonological representations and the efficient updating of verbal information in WM. (Vandermosten et al., 2010) Neurophysiological and functional asymmetry findings further suggest that phonological performance in dyslexia can be associated with atypical hemispheric specialization, reinforcing the plausibility of multiple neurocognitive routes to reading failure. (Hernandez et al., 2013) Systematic reviews of EEG correlates also indicate consistent, though heterogeneous, neurophysiological signatures associated with developmental dyslexia, supporting the view that subgrouping and task specificity are critical for interpreting biological measures. (Cainelli et al., 2023)

Orthographic factors further complicate the picture by shaping how reading skill is acquired and which cognitive resources are most taxed. Meta-analytic evidence on orthographic depth suggests that the manifestation of dyslexia varies across writing systems, which has direct implications for cross-linguistic generalization of subtyping models and for interpreting WM tasks that use language-specific stimuli. (Carioti et al., 2021) In relatively consistent orthographies, reading speed limitations may become a more salient marker, whereas in deeper orthographies, accuracy and irregular word handling may play a larger role; these pressures can differentially recruit WM and attentional resources. (Carioti et al., 2021; O'Brien & Yeatman, 2021) Within such cross-linguistic considerations, subtyping frameworks that distinguish perceptual/visual-attentional versus linguistic/phonological profiles can be especially useful, as they allow researchers to test whether WM differences are driven primarily by verbal coding

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constraints, by executive control limitations, or by broader attentional bottlenecks that influence serial decoding under time pressure. (Germano & Capellini, 2025; Shany et al., 2023; Tarabya et al., 2025)

Despite advances, several gaps remain. First, although WM–reading links are well established, it remains unclear when and under what task conditions dyslexia subgroups diverge in verbal WM performance. (Gray et al., 2019; Peng et al., 2018) Second, many studies focus on single WM indices, whereas theory suggests that WM performance should be examined across graded load levels to identify threshold effects and differential susceptibility to interference. (Baddeley, 2017; Cowan, 2012) Third, comorbid attention problems can inflate estimates of executive dysfunction in dyslexia, and meta-analytic work indicates that ADHD comorbidity meaningfully affects executive functioning outcomes; thus, careful screening is necessary to isolate dyslexia-related mechanisms. (Lonergan et al., 2019; Maehler & Schuchardt, 2016) Fourth, dyslexia has broader psychosocial consequences; individuals with reading difficulty histories may show elevated anxiety and altered self-efficacy, making precise characterization and targeted intervention ethically and clinically important. (Elgendi et al., 2021) Finally, interventions differ in mechanism and efficacy: visuo-attentional training approaches have shown promise in some reviews, while neuropsychological treatment outcomes can depend on matching treatment type to learner profile, underscoring the applied value of valid subgroup identification. (Lorusso et al., 2011; Peters et al., 2019)

Methodologically, rigorous subgroup research requires valid assessment and careful control of confounds such as general intelligence. Raven's Colored Progressive Matrices has been widely used for nonverbal intelligence estimation and has established normative and reliability evidence across contexts. (Bildiren, 2017; Cotton et al., 2005) Standardization and psychometric work in Iran further supports its applicability for elementary school populations, which is crucial for ensuring that observed group differences are not attributable to general cognitive ability differences. (Rasouli Foshtami et al., 2022) Furthermore, the developmental literature indicates that components of WM (including integrative buffers and updating mechanisms) show age-related trajectories linked to word recognition, implying that age and schooling must be considered when comparing dyslexia groups. (Nevo & Bar-Kochva, 2015; Wang et al., 2015) Foundational work also shows that both verbal and visuospatial WM can predict children's reading ability, reinforcing the need to interpret verbal N-back performance within a broader WM architecture that includes modality-specific stores and domain-general control. (Logie, 2014; Pham & Hasson, 2014)

Within this conceptual and empirical landscape, examining load-dependent verbal working memory performance across dyslexia subgroups provides a direct test of whether WM impairment in dyslexia is global and stable or conditional and subgroup-specific. A load-manipulated N-back paradigm is well-suited to this purpose because it can parametrically increase updating demands and interference, thereby revealing whether subgroup differences emerge primarily at higher loads. (Leopold et al., 2024; Mencarelli et al., 2019; Owen et al., 2005) At the same time, interpreting subgroup differences requires anchoring to multifactorial models that incorporate phonological, attentional, and executive constraints, rather than attributing findings to a single pathway. (Lorusso & Toraldo, 2023; O'Brien & Yeatman, 2021; Ziegler et al., 2020) Clarifying these patterns is also practically consequential because it can inform whether interventions should prioritize phonological recoding, visual-attentional dynamics, executive control training, or integrative, personalized combinations. (Lorusso et al., 2011; Peters et al., 2019; Ziegler et al., 2020)

The aim of the present study was to compare verbal working memory performance under different cognitive load levels (0-back, 1-back, and 2-back) between perceptual and linguistic subgroups of Persian-speaking children with developmental dyslexia.

2. Methods and Materials

2.1. *Study Design and Participants*

In this causal–comparative study, 35 Persian-speaking children (19 boys and 16 girls) aged between 7 and 10 years with a diagnosis of dyslexia participated. Participants were selected through purposive sampling from learning disorder centers in the city of Birjand. The initial diagnosis of dyslexia was confirmed based on the criteria of the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) and below-norm performance on the Reading Assessment Test developed by Pour-Etemad and Jahani (2001). Inclusion criteria were as follows: (a) obtaining a score below 71 on the reading test; (b) having an intelligence quotient within the normal range according to Raven's Colored Progressive Matrices; (c) age between 6 and 12 years; (d) absence of neurological disorders (e.g., epilepsy), sensory impairments, or psychiatric disorders; (e) no use of medications affecting cognitive functioning; and (f) documented lack of response to early literacy interventions. Exclusion criteria included: (a) diagnosis of Attention-Deficit/Hyperactivity Disorder (ADHD) based on the parent version of the Conners Rating Scale; and (b) the presence of comorbid neurodevelopmental disorders.

After obtaining ethical approval from the Ethics Committee of Ferdowsi University of Mashhad and securing informed parental consent, purposive sampling was conducted. A semi-structured interview with parents was first performed to examine developmental history and verify inclusion and exclusion criteria. Parents also completed the Conners Parent Rating Scale to screen for Attention-Deficit/Hyperactivity Disorder (ADHD). Preliminary vision and hearing screenings were conducted to ensure sensory integrity. Individual assessment sessions were held in a controlled environment free from distracting stimuli. The order of test administration was identical for all participants and included Raven's Colored Progressive Matrices, the Reading Test (Pour-Etemad & Jahani, 2018), and the verbal N-Back working memory task.

Children were classified into perceptual and linguistic dyslexia subgroups based on Baker's Balance Model (1985) using quantitative data derived from the reading assessment. Classification relied on two dimensions: reading speed and qualitative–quantitative analysis of error patterns. Children whose reading speed fell below the median and whose error patterns were primarily time-consuming (e.g., analytic decoding, rereading, pauses, and self-corrections) were assigned to the perceptual subgroup. Conversely, children with reading speed near or above the median but whose errors were predominantly fundamental or phonological (e.g., omissions, reversals, additions, transpositions, and phoneme or syllable substitutions) were classified within the linguistic subgroup.

2.2. Measures

Raven's Colored Progressive Matrices Test: This test, recognized as an estimate of the nonverbal component of general intelligence (g factor), was designed to assess the development of abstract and inductive reasoning in children. The original test was introduced by John C. Raven in 1938 (Cotton et al., 2005). The instrument is appropriate for children aged 5 to 11 years and consists of 36 pictorial items organized into three sets of 12 items each (Sets A, Ab, and B). Each set begins with simple items and gradually increases in complexity. The child's task is to complete the missing portion of each matrix by selecting the correct option from six alternatives. Scoring is based on the number of correct responses, and total scores are interpreted according to age-based norms (Rasouli Foshtami et al., 2022). International studies have reported internal consistency reliability of 0.83 and test–retest reliability of 0.80 (Bildiren, 2017). Concurrent validity has been supported through significant correlations with the Bender–Gestalt Visual–Motor Perception Test (r = 0.70) and the Naglieri Nonverbal Intelligence Test (r = 0.64). In Iran, Rasouli Fashtami et al. (2022) reported acceptable reliability (Cronbach's alpha = 0.70) and concurrent validity (r = 0.78 with the Stanford–Binet Intelligence Scale), supporting its suitability for the present study.

Reading Ability Test: Participants' reading ability was assessed using the Assessment of Persian Reading Ability (APRA) developed by Pour-Etemad and Jahani (2001). This Persian reading assessment includes 11 texts designed to evaluate reading accuracy, reading speed, and reading comprehension. In addition, three categories of reading errors are identified. Visual errors include omissions (partial or complete deletion of a word), additions (insertion of an extra word or letter), and reversals (letter inversion within a word). Phonological errors include mispronunciation, substitution (replacement with an incorrect word sharing the same initial phoneme), and segmentation (breaking words into components and recombining them during reading). Operational errors include refusal (a 5–7 second pause without an attempt to read) and repetition (re-reading an entire word). Two texts are provided for each grade level from first to fifth grade, along with one preliminary practice text. After reading each text, participants answered comprehension questions, which were used to compute comprehension scores. Reading speed was calculated based on the time spent reading each text, while reading accuracy scores were obtained by counting the number of correctly read words during oral reading. Statistical analyses indicate high reliability and validity for this instrument. Reliability was calculated using Cronbach's alpha and parallel-forms methods. Cronbach's alpha coefficients were 0.90 (even forms) and 0.80 (odd forms) for reading accuracy, 0.80 and 0.70 for comprehension, and 0.90 and 0.80 for reading speed, respectively. Parallel-forms reliability for reading accuracy, reading speed, and comprehension was approximately 0.90. Convergent validity was established through correlations between Persian reading scores and total reading accuracy scores ($r = 0.50$, $p < .001$). Construct validity coefficients ranged from 0.60 to 0.90 for reading

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accuracy, 0.70 to 0.90 for odd forms, 0.30 to 0.60 for comprehension in even forms, 0.30 to 0.50 for comprehension in odd forms, and 0.80 to 0.90 for reading speed.

N-Back Working Memory Task: The N-Back task was first introduced by Kirchner in 1985. Because it simultaneously engages information maintenance and manipulation processes in working memory, it is considered a standard and widely used assessment tool. The task was administered at three levels of complexity (0-Back, 1-Back, and 2-Back) using PsychoPy software. The stimuli consisted of 14 Persian letters (e.g., “ز”, “س”, “ب”). Each stimulus was presented on the screen for 500 milliseconds, followed by a blank screen displaying a fixation cross for 3,500 milliseconds before the next stimulus appeared. In the 0-Back condition, a predetermined target letter (e.g., “ژ”) was introduced, and participants were instructed to press the spacebar whenever that letter appeared. This condition served as a baseline measure of reaction time and simple processing accuracy. In the 1-Back condition, participants pressed the spacebar if the current letter matched the immediately preceding letter. In the 2-Back condition, participants responded when the current stimulus matched the stimulus presented two trials earlier. Before each block, instructions and a training example were provided, and participants were required to complete a practice block successfully to ensure accurate comprehension of the task instructions. The dependent variables included: (a) accuracy score, calculated as the difference between Hit Rate and False Alarm Rate; and (b) mean reaction time for correct responses to target stimuli. Errors were recorded as omissions (failure to respond to a target) and false alarms (responses to non-target stimuli).

2.3. Data Analysis

Data analysis was conducted using IBM SPSS Statistics software. Initially, descriptive statistics (means, standard deviations, skewness, and kurtosis) were calculated to summarize participant characteristics and study variables. Group equivalence in demographic variables was examined using independent-samples t tests. Prior to inferential analyses, the assumptions of multivariate analysis were evaluated, including normality of distribution (Shapiro–Wilk test), homogeneity of variances (Levene’s test), and equality of variance–covariance matrices (Box’s M test). To examine differences between perceptual and linguistic dyslexia subgroups across working memory performance indices (accuracy and reaction time at different cognitive load levels), a multivariate analysis of variance (MANOVA) with a mixed design was performed. Significant effects were further explored using Bonferroni post hoc comparisons. Statistical significance was determined at $p < .05$, and effect sizes (η^2) along with observed statistical power were reported to facilitate interpretation of practical significance.

3. Findings and Results

To ensure the homogeneity of the perceptual and linguistic groups prior to data analysis, the variables of age, grade level, and intelligence quotient were examined using independent-samples t tests. The results indicated that none of the observed differences were statistically significant ($p > .05$). Therefore, it can be concluded that the two groups were homogeneous in terms of demographic characteristics, and the conditions for comparison in subsequent analyses were equivalent. Accordingly, any potential differences between the groups are attributable solely to the dependent variables, and demographic factors did not contribute to these differences.

Table 1 presents the demographic characteristics of the participants by group. In the perceptual group (P), the proportion of boys was higher than that of girls (66.7% vs. 33.3%), whereas in the linguistic group (L), girls constituted a larger proportion (58.8% vs. 41.2%). Regarding age distribution, the highest frequency in group P was observed at ages 7 and 9 years (each 27.8%), while in group L the majority of participants were 9 years old (47.1%). In terms of grade level, group P primarily consisted of first-grade students (50%), whereas in group L greater concentration was observed in second grade (29.4%) and third grade (35.3%).

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Table 1

Demographic Characteristics of Participants by Group

Variable	Category	Group P Frequency (%)	Group L Frequency (%)
Gender	Boys	12 (66.7%)	7 (41.2%)
	Girls	6 (33.3%)	10 (58.8%)
	Total	18 (100%)	17 (100%)
Age (years)	7 years	5 (27.8%)	2 (11.8%)
	8 years	4 (22.2%)	5 (29.4%)
	9 years	5 (27.8%)	8 (47.1%)
	10 years	4 (22.2%)	2 (11.8%)
	Total	18 (100%)	17 (100%)
Grade Level	Grade 1	9 (50.0%)	4 (23.5%)
	Grade 2	4 (22.2%)	5 (29.4%)
	Grade 3	2 (11.1%)	6 (35.3%)
	Grade 4	3 (16.7%)	2 (11.8%)
	Total	18 (100%)	17 (100%)

Table 2 presents the descriptive statistics of the research variables. The mean intelligence quotient was slightly higher in group L than in group P (109.89 vs. 107.16). In contrast, mean accuracy scores across levels were higher in group P compared to group L. Specifically, the mean accuracy at Level 1 was 0.93 in group P and 0.85 in group L. At Level 2, the mean accuracy of group P (0.78) was slightly higher than that of group L (0.76). At Level 3, a more pronounced difference was observed, with a mean accuracy of 0.82 in group P compared to 0.43 in group L. Regarding processing speed, the means were approximately similar between the two groups, and no substantial differences were observed. Skewness and kurtosis values for most variables were within acceptable ranges.

Table 2

Descriptive Statistics of Research Variables by Group

Group	Statistic	IQ	Accuracy Level 1	Accuracy Level 2	Accuracy Level 3	Speed Level 1	Speed Level 2	Speed Level 3
P	Mean	107.16	0.93	0.78	0.82	1.32	1.51	1.42
	SD	11.15	0.09	0.27	0.25	0.15	0.13	0.15
	Kurtosis	0.00	0.68	1.22	0.48	3.44	-0.91	-0.86
	Skewness	0.14	-1.29	-1.20	-1.27	1.56	-0.11	-0.47
L	Mean	109.89	0.85	0.76	0.43	1.30	1.50	1.46
	SD	10.36	0.20	0.19	0.20	0.14	0.15	0.13
	Kurtosis	-0.39	5.67	0.39	1.47	-0.26	-1.18	-0.23
	Skewness	-1.02	-2.12	-0.90	0.01	0.46	-0.30	0.51

Prior to conducting the primary analysis, all assumptions of multivariate analysis of variance (MANOVA) were examined. The normality of each dependent variable (accuracy and speed at different levels) was assessed using the Shapiro–Wilk test, and normal distribution of the variables was confirmed. Homogeneity of variance–covariance matrices was verified using Box's M test (M-Box = 50.06, p = .894). To examine the assumption of homogeneity of variances, Levene's test was conducted. The results indicated that, for all dependent variables, the significance level exceeded .05 ($p > .05$). Therefore, the assumption of equality of error variances across groups was not violated, and homogeneity of variance was established.

The results of the multivariate analysis of variance are presented in Table 3. The main effect of subgroup on the dependent variables was not statistically significant (Wilks' Lambda = .70, $F(6, 24) = 1.74$, $p = .15$). Similarly, the effects of gender and the subgroup × gender interaction were not statistically significant ($p > .05$). The interaction effect of subgroup × intelligence quotient was also non-significant.

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Table 3

Results of Multivariate Analysis of Variance for the Effect of Dyslexia Subgroup

Effect	Wilks' Lambda	F	Hypothesis df	Error df	p	Effect Size (η^2)	Observed Power
Intercept	0.18	17.80	6	24	.001	0.82	1.00
Subgroup	0.70	1.74	6	24	.15	0.30	0.54
Gender	0.76	1.24	6	24	.32	0.24	0.39
Subgroup × Gender	0.72	1.55	6	24	.21	0.28	0.48
Subgroup × IQ	0.59	1.19	12	48	.32	0.23	0.59

Table 4 presents the results of the within-subjects analysis of variance. A significant difference between groups was observed only for Accuracy Level 3 ($F(5, 29) = 5.82$, $p < .001$, $\eta^2 = .50$, observed power = .98). No significant differences were found at Accuracy Levels 1 and 2. Regarding processing speed, none of the levels demonstrated statistically significant differences between groups ($p > .05$).

Table 4

Results of Multivariate Analysis of Variance for Within-Group Effects

Source	Variable	Sum of Squares	df	Mean Square	F	p	Effect Size (η^2)	Observed Power
Corrected Model	Accuracy Level 1	0.16	5	0.03	1.34	.28	.19	.40
	Accuracy Level 2	0.48	5	0.10	2.09	.10	.26	.61
	Accuracy Level 3	1.49	5	0.30	5.82	.000	.50	.98
	Speed Level 1	0.04	5	0.01	0.30	.91	.05	.11
	Speed Level 2	0.16	5	0.03	1.93	.12	.25	.57
	Speed Level 3	0.09	5	0.02	0.95	.46	.14	.29
Intercept	Accuracy Level 1	0.15	1	0.15	6.32	.02	.18	.68
	Accuracy Level 2	0.06	1	0.06	1.37	.25	.05	.20
	Accuracy Level 3	0.47	1	0.47	9.20	.01	.24	.83
	Speed Level 1	0.66	1	0.66	26.94	.000	.48	1.00
	Speed Level 2	0.75	1	0.75	45.53	.000	.61	1.00
	Speed Level 3	0.39	1	0.39	19.79	.000	.41	.99
Subgroup	Accuracy Level 1	0.04	1	0.04	1.69	.20	.06	.24
	Accuracy Level 2	0.00	1	0.00	0.00	.97	.00	.05
	Accuracy Level 3	0.10	1	0.10	1.91	.18	.06	.27
	Speed Level 1	0.00	1	0.00	0.09	.77	.00	.06
	Speed Level 2	0.07	1	0.07	3.97	.06	.12	.49
	Speed Level 3	0.00	1	0.00	0.01	.92	.00	.05
Gender	Accuracy Level 1	0.02	1	0.02	0.70	.41	.02	.13
	Accuracy Level 2	0.19	1	0.19	4.23	.05	.13	.51
	Accuracy Level 3	0.00	1	0.00	0.01	.92	.00	.05
	Speed Level 1	0.00	1	0.00	0.10	.75	.00	.06
	Speed Level 2	0.00	1	0.00	0.20	.66	.01	.07
	Speed Level 3	0.03	1	0.03	1.71	.20	.06	.24
Subgroup × Gender	Accuracy Level 1	0.05	1	0.05	1.96	.17	.06	.27
	Accuracy Level 2	0.20	1	0.20	4.29	.05	.13	.52
	Accuracy Level 3	0.00	1	0.00	0.07	.79	.00	.06
	Speed Level 1	0.03	1	0.03	1.15	.29	.04	.18
	Speed Level 2	0.10	1	0.10	5.91	.02	.17	.65
	Speed Level 3	0.01	1	0.01	0.35	.56	.01	.09
Subgroup × IQ	Accuracy Level 1	0.04	2	0.02	0.90	.42	.06	.19
	Accuracy Level 2	0.03	2	0.02	0.33	.72	.02	.10
	Accuracy Level 3	0.16	2	0.08	1.57	.23	.10	.30
	Speed Level 1	0.01	2	0.00	0.13	.88	.01	.07
	Speed Level 2	0.07	2	0.03	2.11	.14	.13	.40
	Speed Level 3	0.04	2	0.02	1.05	.36	.07	.22
Error	Accuracy Level 1	0.71	29	0.02				
	Accuracy Level 2	1.33	29	0.05				
	Accuracy Level 3	1.48	29	0.05				

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	Speed Level 1	0.71	29	0.02
	Speed Level 2	0.48	29	0.02
	Speed Level 3	0.57	29	0.02
Total	Accuracy Level 1	28.71	35	
	Accuracy Level 2	22.41	35	
	Accuracy Level 3	16.82	35	
	Speed Level 1	60.68	35	
	Speed Level 2	79.91	35	
	Speed Level 3	73.03	35	
Corrected Total	Accuracy Level 1	0.87	34	
	Accuracy Level 2	1.81	34	
	Accuracy Level 3	2.97	34	
	Speed Level 1	0.74	34	
	Speed Level 2	0.63	34	
	Speed Level 3	0.67	34	

Table 5 presents the results of the Bonferroni post hoc test. A statistically significant difference between groups was observed only for Accuracy Level 3 (Mean Difference = 0.375, p < .001, 95% CI [0.21, 0.54]). No significant differences were found for Accuracy Levels 1 and 2 or for processing speed across all three levels.

Table 5

Bonferroni Post Hoc Test Results

Dependent Variable	Comparison	Mean Difference	Standard Error	p	Lower CI	Upper CI
Accuracy Level 1	P − L	0.08	0.06	.14	-0.03	0.20
	L − P	-0.08	0.06	.14	-0.20	0.03
Accuracy Level 2	P − L	-0.03	0.08	.71	-0.18	0.13
	L − P	0.03	0.08	.71	-0.13	0.18
Accuracy Level 3	P − L	0.375	0.08	.0001	0.21	0.54
	L − P	-0.375	0.08	.0001	-0.54	-0.21
Speed Level 1	P − L	0.01	0.06	.80	-0.10	0.13
	L − P	-0.01	0.06	.80	-0.13	0.10
Speed Level 2	P − L	0.02	0.05	.63	-0.07	0.11
	L − P	-0.02	0.05	.63	-0.11	0.07
Speed Level 3	P − L	-0.02	0.05	.67	-0.12	0.08
	L − P	0.02	0.05	.67	-0.08	0.12

Overall, the results indicated that the perceptual group (P) demonstrated superior performance relative to the linguistic group (L) in the accuracy index, particularly at Accuracy Level 3, where a statistically significant and substantial difference was observed. Although the mean intelligence quotient was slightly higher in the linguistic group, this difference was not statistically significant. Furthermore, no differences between groups were observed in processing speed across any level.

4. Discussion

The present study examined whether verbal working memory performance differs between perceptual and linguistic subgroups of children with developmental dyslexia under varying levels of cognitive load. The findings revealed a clear and theoretically meaningful pattern. Although the two subgroups demonstrated comparable performance at lower cognitive load levels, a significant divergence emerged under high-load conditions, particularly in Accuracy Level 3 of the N-Back task. Specifically, the perceptual subgroup outperformed the linguistic subgroup in accuracy, while reaction time did not significantly differ between groups. These results suggest that working memory impairment in dyslexia is not uniform but instead depends on both subgroup characteristics and task demands.

The absence of significant differences at lower cognitive load levels aligns with contemporary multifactorial models of dyslexia, which argue that deficits often remain latent until task complexity exceeds individual processing capacity. (Lorusso & Toraldo, 2023; O'Brien & Yeatman, 2021) Working memory theories propose that performance differences become observable when executive control, updating, and interference management demands increase beyond simple storage processes. (Baddeley, 2017; Cowan,

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2012) In the present study, tasks with minimal cognitive load likely relied primarily on basic maintenance processes, allowing both subgroups to perform similarly. However, as cognitive load increased, subgroup-specific constraints became evident, indicating that linguistic dyslexia may involve vulnerabilities in executive or phonological working memory mechanisms rather than generalized cognitive weakness.

The significant deficit observed in the linguistic subgroup under high cognitive load is consistent with research demonstrating that phonological working memory and central executive functions are disproportionately affected in dyslexia. (Alt et al., 2022) Previous studies have shown that children with dyslexia display reduced efficiency in verbal working memory updating and manipulation processes, particularly when tasks require simultaneous storage and processing. (Wang et al., 2022) Meta-analytic findings also confirm a strong relationship between reading ability and working memory capacity, supporting the interpretation that increased task demands expose underlying linguistic processing limitations. (Peng et al., 2018) In this context, the poorer performance of the linguistic subgroup likely reflects increased susceptibility to phonological interference during verbal updating operations.

Importantly, the findings support subgroup models distinguishing between linguistic/phonological and perceptual/visual profiles of dyslexia. Research proposing phonological and visual parameters as bases for dyslexia subtypes suggests that different cognitive architectures underlie reading difficulties across individuals. (Germano & Capellini, 2025) Studies validating accuracy- versus rate-based dyslexia classifications similarly demonstrate that reading subtypes exhibit distinct processing patterns rather than varying degrees of a single deficit. (Shany et al., 2023; Tarabya et al., 2025) The present results extend these findings by demonstrating that subgroup differences are observable not only in reading behavior but also in domain-general cognitive processes such as working memory when cognitive load increases.

The relatively preserved performance of the perceptual subgroup at higher load levels may reflect compensatory reliance on visual-attentional mechanisms rather than phonological rehearsal strategies. Visual attention theories propose that dyslexic individuals with perceptual profiles may show difficulties related primarily to attentional distribution and temporal sampling rather than phonological storage capacity. (Stein, 2019; Vidyasagar, 2019) Meta-analytic evidence indicates that visual-spatial attention plays an important role in reading development and may support performance under demanding cognitive conditions. (Gavril et al., 2021) Thus, perceptual dyslexia may involve deficits affecting reading speed or visual scanning while leaving certain executive working memory operations comparatively intact.

The lack of significant group differences in reaction time further clarifies the nature of subgroup variation. Equivalent processing speed across groups suggests that the observed differences were not attributable to general slowing or motor response differences but instead reflected accuracy-related cognitive constraints. This interpretation aligns with neuroimaging and behavioral evidence showing that working memory load primarily affects accuracy when executive updating demands increase. (Owen et al., 2005; Rottschy et al., 2012) Studies examining neural activation during N-Back tasks demonstrate that increasing load selectively recruits frontoparietal control networks, emphasizing that performance differences are more closely tied to executive efficiency than to simple processing speed. (Leopold et al., 2024; Mencarelli et al., 2019)

Another important implication concerns the non-significant role of intelligence quotient in explaining subgroup differences. Although the linguistic group demonstrated slightly higher mean IQ scores, this difference was not statistically meaningful, indicating that working memory differences were independent of general intelligence. This finding supports the conceptual distinction between intelligence and specific learning disorders emphasized in diagnostic frameworks. (American Psychiatric, 2013) It also confirms that working memory limitations represent domain-specific cognitive vulnerabilities rather than reflections of global intellectual ability. The use of standardized nonverbal intelligence assessment tools with demonstrated reliability and validity strengthens confidence in this interpretation. (Bildiren, 2017; Cotton et al., 2005; Rasouli Foshtami et al., 2022)

From a developmental perspective, the results align with longitudinal evidence indicating that working memory contributes to reading acquisition trajectories. Early working memory abilities have been shown to predict later reading performance, suggesting that subgroup differences may represent divergent developmental pathways rather than temporary performance variations. (Nevo & Bar-Kochva, 2015) Research examining episodic buffer development further indicates that integration of phonological and semantic information becomes increasingly demanding with age, making load-sensitive tasks particularly useful for

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identifying latent deficits. (Wang et al., 2015) Consequently, the emergence of subgroup differences only under high load may reflect developmental thresholds at which compensatory mechanisms fail.

Neurocognitive findings also provide converging support. Neurophysiological studies indicate atypical hemispheric specialization and altered phonological processing networks in dyslexia, which could explain why linguistic subtypes struggle when verbal information must be actively manipulated. (Hernandez et al., 2013) EEG reviews similarly emphasize heterogeneous neural signatures across individuals with dyslexia, reinforcing the importance of subgroup analysis rather than treating dyslexia as a homogeneous condition. (Cainelli et al., 2023) Evidence of auditory temporal processing deficits further suggests that inefficient encoding of phonological information may increase cognitive load during working memory tasks. (Vandermosten et al., 2010)

The present findings also resonate with broader executive functioning research indicating that dyslexia-related executive deficits may emerge primarily when attentional control and interference management are taxed. Meta-analytic work demonstrates that executive functioning weaknesses are especially pronounced when comorbid conditions are controlled, suggesting that dyslexia-specific executive vulnerabilities exist independently of ADHD. (Lonergan et al., 2019; Maehler & Schuchardt, 2016) The screening procedures employed in this study likely contributed to isolating these dyslexia-related mechanisms, enabling clearer interpretation of subgroup differences.

Educational implications emerge directly from these findings. If working memory deficits vary by dyslexia subtype, uniform intervention programs may fail to address individual needs. Intervention research indicates that treatment effectiveness depends strongly on matching intervention strategies to underlying cognitive profiles. (Lorusso et al., 2011) Reviews of visuo-attentional training approaches further show that interventions targeting specific mechanisms can improve reading outcomes when aligned with learner characteristics. (Peters et al., 2019) Computational models of reading development similarly emphasize personalization as a key principle for effective remediation. (Ziegler et al., 2020) Thus, subgroup-sensitive assessment frameworks may represent an essential step toward precision education in dyslexia.

Beyond cognitive performance, dyslexia also carries psychosocial implications. Individuals with reading difficulties often experience reduced academic self-efficacy and elevated anxiety, which can exacerbate learning challenges if cognitive needs remain unidentified. (Elgendi et al., 2021) By clarifying the cognitive architecture underlying subgroup differences, educators and clinicians may better design interventions that prevent secondary emotional consequences associated with persistent academic failure.

In summary, the present findings provide empirical support for the hypothesis that verbal working memory impairment in dyslexia is load-dependent and subgroup-specific. Linguistic dyslexia appears particularly vulnerable under high cognitive load conditions requiring active verbal updating, whereas perceptual dyslexia may involve different processing constraints not captured by accuracy measures in verbal working memory tasks. These results strengthen multifactorial accounts of dyslexia and highlight the importance of integrating cognitive load paradigms into diagnostic and intervention frameworks.

Several limitations should be acknowledged. First, the sample size was relatively modest, which may have limited statistical power for detecting smaller subgroup effects, particularly interaction effects involving gender or intelligence. Second, the cross-sectional design prevents causal interpretation regarding developmental changes in working memory functioning. Third, although participants were carefully screened for major comorbid conditions, subtle attentional or emotional factors may still have influenced performance. Fourth, the study relied on a single verbal working memory paradigm, and inclusion of additional tasks assessing visuospatial or complex executive functioning might have provided a more comprehensive cognitive profile. Finally, the findings are limited to Persian-speaking children and may not fully generalize across orthographies or cultural contexts.

Future research should employ larger longitudinal samples to investigate how working memory differences evolve across developmental stages and educational experiences. Studies integrating behavioral, neurophysiological, and neuroimaging measures could clarify neural mechanisms underlying subgroup distinctions. Comparative investigations across orthographic systems would also help determine whether load-dependent working memory differences represent universal characteristics of dyslexia or language-specific adaptations. Additionally, future work should examine how intervention responsiveness varies across subgroups, particularly in relation to executive training, phonological therapy, and visual-attentional programs. Incorporating ecological

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academic measures such as reading comprehension, writing fluency, and classroom performance would further enhance external validity.

Educational and clinical assessment procedures should move beyond single-score diagnostic approaches and incorporate cognitive load–sensitive working memory measures to identify distinct learner profiles. Individualized intervention planning should consider whether a child demonstrates linguistic or perceptual characteristics and select instructional strategies accordingly. Teachers and school psychologists may benefit from integrating working memory supports into classroom instruction, including structured presentation of information, reduced cognitive overload, and multimodal learning strategies. Early screening programs should emphasize cognitive profiling rather than solely focusing on reading outcomes, enabling preventive intervention before academic difficulties become entrenched. Finally, collaboration among educators, clinicians, and families is essential to translate cognitive assessment findings into practical and sustainable educational support plans.

5. Conclusion

Overall, the findings of the present study are consistent with emerging trends in cognitive and educational interventions that emphasize personalization, adaptability, and inclusivity. Advances in technology-based and AI-supported cognitive training programs have highlighted the potential for scalable and individualized interventions for learners with diverse needs (Gadekallu et al., 2025; Shao et al., 2025). Although the present study employed a non-digital, group-based working memory training program, the underlying principles of progressive challenge, feedback, and executive engagement align closely with these newer approaches. As such, the results provide a theoretically grounded rationale for integrating working memory training into both traditional and technology-enhanced intervention frameworks for students with specific learning disorder.

Despite these promising findings, several limitations of the present study should be acknowledged. The sample size was relatively small and drawn from a single urban context, which may limit the generalizability of the results to broader populations of students with specific learning disorder. Additionally, although a follow-up assessment was included, the follow-up period was relatively short, and longer-term outcomes remain unclear. The reliance on standardized neuropsychological and rating-scale measures, while methodologically sound, may not fully capture changes in real-world academic performance or classroom behavior. Furthermore, the study did not examine potential moderating variables such as severity of learning disorder, comorbid conditions, or family involvement, which may influence responsiveness to intervention.

Future research should aim to replicate these findings with larger and more diverse samples, including students from different age groups, educational settings, and cultural backgrounds. Longitudinal designs with extended follow-up periods would be valuable for assessing the long-term sustainability of working memory training effects and their impact on academic trajectories. Future studies may also benefit from comparing different types of cognitive training programs, including computerized, adaptive, and hybrid interventions, to determine which approaches yield the strongest and most transferable outcomes. Additionally, examining potential moderators and mediators of intervention effectiveness, such as baseline executive function levels, motivation, and parental involvement, could provide deeper insight into for whom and under what conditions working memory training is most effective.

From a practical perspective, the findings of the present study suggest that working memory training can be meaningfully integrated into educational and rehabilitation programs for students with specific learning disorder. Educators, school psychologists, and therapists may consider incorporating structured working memory exercises into individualized education plans and remedial curricula. Emphasis should be placed on consistency, gradual increase in task complexity, and opportunities for applying trained skills to academic activities. Collaboration between schools and families may further enhance the effectiveness of such interventions by promoting the generalization of cognitive skills across settings and supporting students' ongoing engagement in the training process.

Authors' Contributions

Authors equally contributed to this article.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

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Declaration of Interest

The authors report no conflict of interest.

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Ethics Considerations

The study protocol adhered to the principles outlined in the Helsinki Declaration, which provides guidelines for ethical research involving human participants (Ethics code: IR.UM.REC.2025.303).

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